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Objective Measures of IS Usage Behavior Under Conditions of Experience and Pressure Using Eye Fixation Data

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Abstract

The core objective of this study is to understand individuals IS usage by going beyond the traditional subjective self-reported and objective system-log measures to unveil the delicate process through which users interact with IS. In this study, we conducted a laboratory experiment to capture users' eye movement and, more importantly, applied a novel methodology that uses the Gaussian mixture model (GMM) to analyze the gathered physiological data. We also examine how performance pressure and prior usage experience of the investigative system affect IS usage patterns. Our results suggest that experienced and pressured users demonstrate more efficient and focused usage patterns than inexperienced and non-pressured ones, respectively. Our findings constitute an important advancement in the IS use literature. The proposed statistical approach for analyzing eye-movement data is a critical methodological contribution to the emerging research that uses eye-tracking technology for investigation.

Keywords: IS use, User behavior, Laboratory experiment, Experience, Pressure to perform, Eye-tracking, Gaussian mixture model

Introduction

Organizations nowadays expect employees to perform their jobs efficiently and effectively so as to survive in this hyper-competitive market. To facilitate employees' day-to-day operation, organizations typically provide them with advanced information systems (IS), as well as training sessions to increase employees' usage experience so as to enhance their ability to apply the implemented IS for work purpose. As such, researchers as well as practitioners have much interest in individual IS usage behavior and its predictors like performance pressure and usage experience.

The IS usage literature has accumulate a rich body of knowledge (Burton-Jones and Straub 2006). However, the possible way to conceive and understand individuals IS usage behaviors is usually constrained (or enabled) by the empirical methods applied to measure this behavior. That said, while researchers generally prefer objective IS usage measures (system log) to subjective measures (e.g., user self-reported IS use), the objective measures used in prior studies are almost all system-based log data (see Table 1). To overcome the limited insights permitted by these extent measures, the emerging psychophysiological tools, such as the eye-tracking device, represent promising opportunities to deepen our understanding of individual IS usage (Dimoka et al.2012). Unfortunately, the IS community has not fully capitalize on this opportunity. To our best knowledge, there has been only one study published in top IS journal using the eye-tracking device (i.e., Cyr et al. 2009). Moreover, the value of the eye-tracking data could be further extracted by using more advanced analytical methods.

Toward this end, we revisited the IS usage literature, developed hypotheses on the effect of performance pressure and experience on IS use, and conducted a lab experiment to objectively investigate individual IS usage behavior using an eye-tracking device to capture users' eye movements. More importantly, we applied a novel methodology that uses a statistical method (Gaussian Mixture Model) to identify users' regions of interest (ROI) and number of views on each ROI, which together are defined as individual IS usage pattern in this study. Our results reveal significant and interesting behavioral differences between experienced and inexperienced users, as well as between pressured and non-pressured ones. In particular, we found that (1) the experienced users, relative to inexperienced ones, are more efficient (in terms of the number of fixations and ROIs) and more focused when using IS to fulfill their tasks, and that (2) pressured users, relative to non-pressured, demonstrate more efficient and focused usage patterns.

Our findings reveal unprecedented insights into individual IS usage pattern and constitute an important advancement in the IS use literature. The proposed statistical approach for analyzing eye movement data is a critical methodological contribution to the emerging research that uses eye-tracking technology for investigation.

Research Background

IS Usage – Conceptualizations and Measures

Over the past three decades, scholars have proposed a variety of conceptualizations and measures of IS usage behaviors (Burton Jones and Jones 2006). Conceptually speaking, Burton-Jones (2005) found that prior studies have examined IS usage as method of use (i.e. direct vs. indirect use), extent of use (i.e. number of systems, sessions, displays, functions used), proportion of use (number of times a system is used to perform a task), duration of use (daily or weekly connecting time), frequency of use (daily or weekly using time), decision to use (use or not use), voluntariness of use (voluntary or mandatory use), variety of use (number of IS-supported tasks), specificity of use (specific or general use), appropriateness of use (appropriate versus inappropriate use), dependence on use (degree of dependence on use), etc.

Methodologically, scholars concern whether IS usage is measured as subjective self-reported user perceptions or objective system-based data. While some measures for IS usage could be gauged objectively, most of the IS usage measures are based on users' perceptions, particularly those measures describing the manners of IS usage (i.e. method, specificity, appropriateness of, and dependence on use) are not observable via system logs. Moreover, only the duration of use and some aspects of the extent of use (i.e. number of systems, sessions, user-generated contents) could be measured based on objective data. In other words, there are limitations of the both existing objective and subjective measures of IS usage.

Pentland (1989) compared self-reported subjective and objective measures of IS usage and concluded that self-reported measures tend to be less accurate than objective measures (Pentland 1989). Table 1 lists studies in premier IS and marketing journals that applying objective IS usage measures. Most applied objective measure for IS usage is the number of requested and accessed reports within an IS. A slight shift can be seen from pure time-based and functionality measures such as connection time (i.e. Ginzberg 1981; Srinivasan 1985), or number system accesses and sessions (i.e. Lucas 1978; Igbaria et al. 1989) to more user-specific measures such as number of blog posts (Wattal et al. 2010), clicks Brynjolfsson et al. (2011), skipped advertisements (Bronnenberg et al. (2010), number of requested and accessed data reports, or computer processing capacity utilized (Devaraj and Kohli 2003).

Table 1. Objective measures of IS usage between 1974-2013	
Measure	**Reference in the literature**
Monitored-single indicator	Swanson (1974)
Number of system queries	King and Rodriquez (1978); DeSanctis (1983); De et al. (2010)
Number of data reports requested, and accessed	Schewe (1976); Benbasat and Schroeder (1978); Raymond (1990); Szajna (1993); Devaraj and Kohli (2000); Devaraj and Kohli (2003)
Number of sessions	Lucas (1978); Ginzberg (1981); Igbaria et al. (1989); Lu and Gustafson (1994), Devaraj et al. (2008)
Frequency of updates	Robey (1979)
Connect time	Ginzberg (1981); Srinivasan (1985); Venkatesh et al. (2002)
Number of system accesses	Srinivasan (1985); Raymond (1990); Lu and Gustafson (1994);
Number of software packages used	Igbaria et al. (1989)
Number of communications (emails)	Szajna (1996); Klein (2007)
Computer processing capacity utilized	Devaraj and Kohli (2003)
Amount of downloaded data	Ahearne et al. (2004)
Number of clicks	De et al. (2010); Brynjolfsson et al. (2011)
Number of skipped advertisements	Bronnenberg et al. (2010)
Number of blog posts	Wattal et al. (2010)
Number of search queries	Brynjolfsson et al. (2011)

Psychophysiological Tools to Observe IS Usage

Albeit the rich body of literature on IS usage, it is an ongoing discussion on how to understand and capture the individuals' IS usage behaviors in a more comprehensive and insightful manner. Toward this end, Dimoka et al. (2012) suggest the use of brain imaging (e.g., fMRI, EEG) and psychophysiological tools (e.g., eye-tracking, skin conductance) for IS research in general and IS usage in particular.

For example, Dimoka and Davis (2008) were able to identify brain activations in the areas associated with perceived usefulness and perceived ease of use regarding an IS and provide evidence on the temporal ordering based on an fMRI study (measurement of neural activity by changes in blood flow). Dimoka et al. (2012) further showed that the cognitive construct "perceived usefulness" may emerge in "emotional" areas of the brain, such as the insular cortex and the anterior cingulate cortex (Dimoka et al. 2012).

Dimoka et al. (2012) further discuss the potential of other psychophysiological tool, including eye-tracking, skin conductance response (SCR), facial Electromyography (fEMG) and electrocardiogram (EKG). While the later three tools can measure psychophysiological reactions that are predominately triggered by feelings and emotions such anxiety, stress, effort, and arousal (Dimoka et al. 2012), there are no IS studies using any of these tools.

Eye-Tracking Tools to Measure IS Usage

The eye-tracking tool can gauge exactly how long and where the human eyes look and focus on a certain stimulus or image on a screen (fixation) and how the eye's motion is relative to the head (eye movement) (Shimojo et al. 2003). For instance, Cyr et al. (2009) applied this method and successfully identified the impacts of website human images on users' perceptions. Despite the potential of the eye-tracking device for IS research, to our best knowledge, the work by Cyr et al. (2009) is so far the only study published in

premier IS journal using this device. From a researcher's point of view, instead of providing subjective perceptions or objective observation on the black box of individual IS usage, the eye-tracking tool provides objective statements and visualizations on what exactly happen during an individual's direct interaction with an IS, thereby offering a much more insightful and nuanced understanding with regard to individuals' IS usage. These insights could help understand causality issues related to IS usage such as the impact of prior usage experience or pressure to perform on individuals' IS usage patterns.

While eye-tracking tool can generate a rich amount of data on users' visual patterns, the analytical approaches applied for analysis determine the insights that researchers can extract from the data. To advance this line of research, we apply an advanced analytical skill, i.e., the Gaussian Mixture Model (GMM), to analyze the gathered eye tracking data. The results of this analysis reveal users' eye movement in terms of users' regions of interest and the number of views on each region of interest (ROI), which together are referred to as individuals' IS usage patterns.

Hypotheses Development

Key Terms

All terms theoretically hypothesized and objectively measured in this research are defined and explained in the following Table 2.

Table 2. Description of key terms			
Term	**Definition**	**Applied Measure**	**Reference**
Effectiveness (Accuracy)	A dimension of performance referring to the extent to which a user's has attained the goals of the task for which the system was used.	measured in this research as binary variable if the task is fulfilled right or wrong	Burton-Jones and Straub (2006)
Efficiency	A dimension of performance referring to the extent of goal attainment for a given level of input (such as effort or time).	measured in this research as number of total fixations and total time per task	Gattiker and Goodhue (2005)
Usage pattern	Usage patterns represent different extents to which features in the system are used.	measured in this research as users' eye movement in terms of users' regions of interest (ROI) and the number of views on each ROI	DeSanctis and Poole (1994)
Experience	Experience stands for the amount of time spent, frequency, or a combination of amount and frequency using a specific IS in the past.	measured in this research if the individual has used the system before or not	Varna and Marler (2013)
Pressure to Perform	Pressure to perform refers to externally set objectives in terms of efficiency/effectiveness affecting individuals' performance.	measured in this research if the individual has incentives to perform and the instruction to perform fast and accurate	Baumeister (1984)

Experience as Direct Determinant of IS Usage Behavior

A rich body of literature has revealed that prior IS usage experience (referred to as experience for short) is not only an important determinant for the use of the same IS artifact but also those of similar ones (e.g., Varma and Harler 2013). In this study, experience stands for the amount of time spent, frequency, or a

combination of amount and frequency using a specific IS in the past (Varna and Marler 2013).

Some studies have revealed that this relationship is very strong (e.g., Kim and Malhotra 2005; Kim 2009). In the context of IS use by knowledge workers, Thompson et al. (1994) stated that "*it would be surprising if a strong correlation was not observed between experience with personal computers (past behavior) and current utilization.*" While these studies proved that prior usage experience is an important driver for actual IS usage behavior, almost nothing has been done so far to uncover what this definite impact on usage behavior looks like in terms of different usage patterns. To provide some first insights on how to close this research gap and what these differing behavioral patterns might look like, we provide the results of a laboratory experiment using eye-tracking technology and evaluate this data using a novel methodology based on a statistical model, the Gaussian mixture model (GMM). The hypotheses of our research are outlined below.

Hypotheses for the Impact of Experience on IS Usage Patterns

Within the lab experiment we took the perspective of an employer who has recently implemented a new information system for their employees to get tasks done. Especially under the current economic conditions, the corporate objective that user tasks shall be done as quick and as correct as possible certainly best reflects the real organizational environment in practice.

As outlined in the previous subsections, experience determines how individuals evaluate a particular technology. From the perspective of memory, sensory memory already gathered through prior usage experiences using a particular IS are stored as implicit procedural memory; this memory helps individuals to use this system at a later point in time (Kim 2009). This implicit memory could include information on the system's functionalities, procedures and outcomes. Hence, we expect differential usage patterns between experienced and non-experienced users.

H1a: Experienced users have significantly different IS usage patterns compared to users without prior experience.

Human-computer interaction research suggests that differences in experience were an important factor in efficient computer interaction, meaning that experience helped users to fulfill their interaction tasks more quickly. This is due to the effect that experienced users know a particular system and its related procedures. They are able to store important functionalities as the location and functions of the tool bar, the variety of drop-down or drag and drop menus, or the location of the content search function in sensor memorizing processes (Kim 2009). Also more experience will usually lead to more accurate and faster task performance (Bak and Meyer 2011). Kang and Yoon (2008) showed that learning leads to improved performance accuracy and shorter performance times after users gained some experience with the system. Finally, Guimaraes and Igbaria (1997) found in their user observations that end-user computer experience has a strong direct effect on the variety of tasks of general system usage, meaning that experienced users could be able to transform their implicit memory of prior system usage into their actual usage patterns.

H1b: Experienced users are significantly more efficient and more focused in their IS usage behavior compared to users without prior experience.

Pressure to Perform as Direct Determinant for Usage Behavior

Compared to usage experience and its influence on individual IS usage, research on how pressure to perform affects IS usage is rather limited. In general, pressure to perform refers to externally set objectives for an individual's behavior in general, and task fulfillment in particular. These targeted objectives (e.g., for efficiency in terms of time, and for effectiveness in terms of output quality) constrain individual behavioral actions and affect performance. Within research approaches analyzing IS usage behavior just two major theoretical perspectives are known and investigated so far. First, based on the Theory of Reasoned Action and its extension the Theory of Planned Behavior the concept "*...subjective norm refers to the perceived social pressure to perform or not to perform the behavior...*" (Ajzen 1991). This form of pressure to perform comes from an individual's social environment. It is solely internalized and perceived by the individual, meaning that this sort of pressure to perform has not necessarily been applied beforehand (Ajzen 1991). The second understanding of pressure to perform in IS usage research concerns the concept of time pressure. In many occupations, decision making under time pressure by

using a computer is a part of many individuals' daily business. Encouraging individuals to make decisions within a limited time period may pressure and stress them. Marsden et al. (2002, 2006) observed decision-making under pressure with different information sources and performance-based financial incentives. In these approaches, the researchers aimed to identify the differential impact of implicit and explicit pressure. A constructed reward/penalty structure was implemented that seeks to apply sustained, implicit pressure on subjects by valuing speedy decision accuracy more than tardy accuracy, tardy accuracy more than tardy inaccuracy, and tardy inaccuracy more than speedy inaccuracy. By letting participants fulfill three different tasks of increasing complexity, the authors also exerted explicit time pressure. Their results revealed that focusing more on objective data might help to understand the influence of pressure better, as the results for the impact of implicit and explicit pressure largely varied (Marsden et al. 2002; Marsden et al. 2006).

Hypotheses for the Impact of Pressure to Perform on IS Usage Patterns

Pressure to perform can make individuals to behave differently. Although, Fisher at al. (2003) did not find any differences for non-IS-supported decision-making between pressured and non-pressured groups, they discovered significant differences between the two groups as long as the decision-making is supported by information systems. Many recent studies have also observed the use of IS correlates with the amount of pressure felt by users (Kang and Yoon 2008; Ragu-Nathan et al. 2008; Ayyagari et al. 2011).

H2a: Pressured users have significantly different usage patterns compared to users without pressure to perform.

In general, pressure affects how individual behaviors. When users are rewarded for faster and better task accomplish (i.e., using incentive as a form of pressure (e.g., Dohmen 2008)), they may need to rethink their next usage steps faster. This requires them to keep focus on system functionalities, helping them to reach next steps faster than just trying and testing their adequacy. Although this may lead to lower accuracy (Ahituv et al. 1998), it may enhance their efficiency in terms of speed. Those who feel rushed will spend a significantly higher proportion of their time on their task fulfillment, and a significantly lower proportion on other acts like watching around and exploring the surroundings (De Grada et al 1999). Such pressure might also lead to more task focus, as some individuals will judge some information to be less important during their decision processes. A similar process has also been observed that individuals become more worried about making a fast and common decision and less worried about other goals, such as improving the quality of the decision or evaluating potential alternatives (Karau and Kelly 1992; Kelly and Loving 2004; Connelly et al. 2013). Hence we expect:

H2b: Pressured users are significantly more efficient (measured in number of fixations) and more focused in their IS usage behavior compared to users without pressure to perform.

Research Methodology

In order to confirm the general (H1a and H2a) and specific hypotheses (H1b and H2b), we run a laboratory experiment where participants had to fulfill tasks in the online career network LinkedIn.com. We set up a neutral account in LinkedIn without any reference to a male or female profile, and with ten real-world contacts not known by the participant. We captured data concerning individuals' demographics as well as prior usage experience using a survey prior to the experiment. While evaluating the eye-tracking data, we split the entire sample of 125 participants according to (a) prior usage experience and (b) pressure to perform into four groups (experienced vs. inexperienced; with pressure to perform vs. without pressure to perform).

Participants Recruitment

The target population of our experimental setting is not limited to any specific occupation. As a consequence of the fact that the population selected for this research is the whole population who are users of technologies, we decided to recruit individuals in different ways. First, we publicized that we were performing an experiment within lectures at our universities. These lectures included about 20 students, who all worked full-time next to their study. Although we asked them to participate within our experiment, the participation was on a voluntary basis. Second, we handed out flyers around the city in order to recruit

individuals of different age and different backgrounds. The data collection started in March 2012 and ended in November 2012.

Survey

Each individual participant had to complete a survey prior to the experiment. They reported demographic data, such as age, gender, working experience, and occupation, and prior LinkedIn usage experience. We classified all individuals into two groups, including non-users, who had never used LinkedIn before, and users, who have been with or are still registered in LinkedIn. Participants of the latter group, as compared to those in former group, were more familiar with the functions and procedures of LinkedIn.

Experimental Design

After an individual had completed the survey, s/he went together with the experimenter into a separated and quiet room, which solely included a PC so that the individual was not distracted by any external influence. Since we used an eye-tracker to observe the individual IS usage behavior, the system had to be configured for each participant. During this time, the experimenter explained why the system is needed, and called attention to the fact that the individual should behave as usual and should not get stressed due to the software. To apply the treatment of pressure to perform, we took the same approach as Marsden et al. (2002; 2006), by integrating a distinct task description. Therefore, the experimenter explained to the individual the upcoming task to be accomplished, whereby we had two different task formulations, which were presented alternately. Both task formulations included that individuals should accomplish the same task in LinkedIn, which are explained in the following paragraphs. Nevertheless, the task formulations were distinguished by the way that the experimenter explained to one group that they should relax, take time to complete the task, and that it is not crucial whether or not the task is completed successfully. To the other group, the experimenter offered this group the incentive to win an iPad, if they finished their task as fast and as good as possible. Based on this procedure, we separated the group between individuals perceiving pressure to perform, and individuals who do not perceive pressure to perform. Using incentives to apply pressure to perform is a common practice in laboratory experiments observing human behavior and performance (Baumeister 1984; Dohmen 2008, DeCaro et al. 2011).

In the experiment, the participants' task consisted of asking one specific person of the ten real-world contacts for a job recommendation. LinkedIn has a functionality allowing its members to provide past co-workers references on the quality of their collaboration during their common time. To reach this function, participants had to open a specific menu point in the dropdown menu of the toolbar named recommendations. We set this task in the experiment with only one possible way to finish, in order avoiding the problem of equifinality. Multiple paths in a system to achieve a specific end and to finish a task successfully would limit our implications for IS usage behavior. While fulfilling this task, we observed participants' objective IS usage behavior by using eye-tracking technology.

Eye-Tracking

Eye-tracking research either focuses on fixations on specific regions of interest, in which the eyes remain motionless, or saccades, which describe situations in which eyes move rapidly (Rayner 1998). During saccades, in which eyes move from one fixation to another one and last between 15 and 40 milliseconds (ms) (Reichle et al. 1998), individuals do not process information because of the rapid eye movements (Rayner 1998). In contrast, information is processed in fixations, which last on average about 225 ms, and a skilled reader can obtain most of the information required for reading within the first 50 ms of a fixation (Rayner et al. 1981; Lankford 2000; Liversedge et al. 2004).

For this research, eye-tracking was performed using the double Eyegaze Edge™ System eye-tracker, paired with a 19" LCD monitor (86 dpi) set at a resolution of 1280x1024, whereby the eye-tracker samples the position of participants' eyes at the rate of 60Hz. The eye-tracker was installed under the monitor and tracked the participant's eyes during the experiment.

Gaussian Mixture Model for Eye-Fixations

We used a data-driven approach to identify ROIs on the webpage for the task. We modeled the

distribution of fixations provided by the eye-tracker as a Gaussian mixture model (GMM), where each Gaussian component corresponds to an ROI on the webpage. Specifically, the distribution of fixation locations in an ROI is modeled as a 2-dimensional Gaussian density,

$$N(x;\mu_j,\Sigma_j) = \frac{1}{2\pi|\Sigma_j|^{1/2}} \exp\left\{-\frac{1}{2}(x-\mu_j)^T \Sigma_j^{-1}(x-\mu_j)\right\},$$

where x is a 2-d vector containing the x- and y-coordinates of the fixation, and μ_j and Σ_j are the mean and covariance matrix of the Gaussian for the jth ROI. The distribution over all ROIs, i.e., on the webpage, is a mixture of 2-d Gaussians,

$$p(x) = \sum_{j=1}^{K} \pi_j N(x;\mu_j,\Sigma_j),$$

where π_j is the probability of looking at the jth ROI, and K is the number of ROIs. In this paper, we used K=7 ROIs, since 7 ROIs seemed to best capture the informative regions used by the participants during the task and reveal their strategies reasonably.

The ROIs were automatically learned from the corresponding eye fixation data for the task[1] using the expectation-maximization (EM) algorithm (Dempster et al. 1977; Bishop 2006) to calculate a maximum likelihood estimate for the GMM parameters. Given the dataset of n fixations, $\{x_1,\cdots,x_n\}$, the EM algorithm iterates between the E-step and M-step until convergence. In the E-step, $\hat{z}_{ij}$ is the probability that the ith fixation (x_i) belongs to the jth ROI, which is then used in the M-step to update the parameters of the GMM. After the ROIs were learned, each fixation x_i was assigned to the ROI with largest probability of generating the fixation

$$R_i = \underset{j \in \{1,\cdots,K\}}{\operatorname{argmax}} \hat{z}_{ij}.$$

The result was a grouping of fixations into a number of distinct ROIs. This method gave us a set of objective ROIs that best reflected participants' strategies in solving the task, in contrast to predefined ROIs used by some previous eye movement studies (e.g., Dreze and Hussherr 2003; Radach et al. 2003; Henderson et al. 2005), which can be biased by experimenters' prior beliefs. This method has been used in analyzing eye movements in face recognition, and shown to better capture individual differences in eye movement strategies in face recognition as compared with using predefined ROIs or heat map analysis (Chuk et al. 2013).

In this study, we aim to use these objective, data-driven ROIs to analyze the similarities or differences in eye fixations on the website LinkedIn made by two groups of participants (e.g., experienced and inexperienced users, as well as pressured and non-pressured users). For a given participant group, a ROI histogram was formed where each bin corresponds to a ROI, and the bin value was the number of fixations made in that ROI by the group during the task. The ROI histogram summarized the fixation patterns for each group while performing the task. The significance of differences between the two ROI histograms was tested using the chi-squared test of independence (Howell 1995). Note that the ROI numbering 1 to K are simply identification numbers, and do not imply a particular order of viewing the ROIs. The estimation of the ROI using GMMs and the calculation of the ROI histogram were implemented in MATLAB.

Research Results

A total of 125 individuals took part in our experiment. The sample was equally distributed concerning participants' gender; 54.4 percent were male and 45.6 percent were female. The age distribution ranged from 21 to 61 years, with an average age of 29.6 years. The majority of the participants had an academic

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[1] We ignore all fixations falling outside of the webpage.

degree (either a Bachelor, Master, or PhD degree). More than 50 percent of all participants were students in a part-time MBA class. We analyzed usage experience with the technology by asking all participants who use the technology in question; participants who answered "seldom" or more frequently were classified as experienced users (the scale for "I use the technology..." ranges from very frequently-frequently-regularly-seldom-never). 90 participants had no prior LinkedIn usage experience, while 36 participants had or have had an active LinkedIn account. All of the 36 participants with prior LinkedIn usage experience can be classified as occasional users. As the treatment of pressure to perform was applied as a focus group treatment before the laboratory experiment for every second participant, the distribution between pressured (62 participants) and non-pressured (63 participants) individuals was almost equal. This data sample represented the basis for the eye fixation data analysis using GMM in order to identify behavioral usage patterns of different groups in terms of ROIs. The results of GMM and the Chi^2-test, as well as the plotted fixations of the different groups are presented in the following subsections.

Results for the Effect of Experience on Behavioral IS Usage Patterns

In the current literature of eye movement research, eye fixation data are typically analyzed by using a set of predefined ROIs according to the experimenter's prior assumptions (e.g., Kroeber-Riel, 1979; Lohse, 1997; Dreze and Hussherr, 2003; Radach et al., 2003). The problem with this approach is that ROIs are subjectively defined without an agreement among studies; it may be also biased by the experimenter's beliefs. Caldara and Miellet (2011) proposed the iMap approach to analyze eye movement data, aiming to overcome the drawbacks of using predefined ROIs. In the iMap approach, a fixation heat map is created by convolving a Gaussian kernel with each fixation; the fixation heat maps of different conditions then can be compared pixel by pixel to determine the locations with significant difference between conditions (see also Sutcliffe and Namoune 2007; Shrestha and Owens 2008; Bojko 2009). However, the problem with this approach is very often the regions with significant difference between conditions can be very scattered and therefore hard to interpret. Another problem with iMap, is that it uses the same Gaussian width for all fixations, which limits its effectiveness to situations where all the ROIs are of similar size. However, for webpages, the size of the ROIs can vary dramatically; some ROIs may be very focused (e.g., the search bar), whereas others are large (e.g., the status updates and ads section). To overcome these problems, here we adopt a data-driven approach to obtain objectively defined ROIs by training a Gaussian mixture model from the data. We then analyze participants' eye fixation patterns through comparing the distribution of their fixations in these objectively defined ROIs in different conditions.

In the current analysis, the GMM identified seven ROIs that best captured participants' eye fixation strategies. As depicted in Figure 1 for the groups of experienced and inexperienced users, these seven ROIs are highlighted in different colors. The first ROI (highlighted in red) primarily focuses on the search function of the network and a button for the immediate adding of new contacts in the network. The second and third ROIs (green and blue) include a window welcoming the user back to the network, as well as a text field for inserting status updates. The fourth ROI (highlighted in magenta) focuses on almost two thirds of the entire webpage containing the user's LinkedIn contacts' status updates, new connections, or occupations, as well as recommendations for jobs or groups in the network they might be interested in; the content of this area was irrelevant to the task. This ROI is very spread out because no particular part of it is informative for the task. The fifth ROI (highlighted in cyan) in the upper left corner includes links to the user's profile and her or his contacts in the network. The sixth ROI (highlighted in yellow) includes functionalities on the toolbar linking to groups, mailbox, companies or the job market in LinkedIn. The last ROI (highlighted in brown) predominately includes users' eye fixations in the website area where they are presented with the other users they might know.
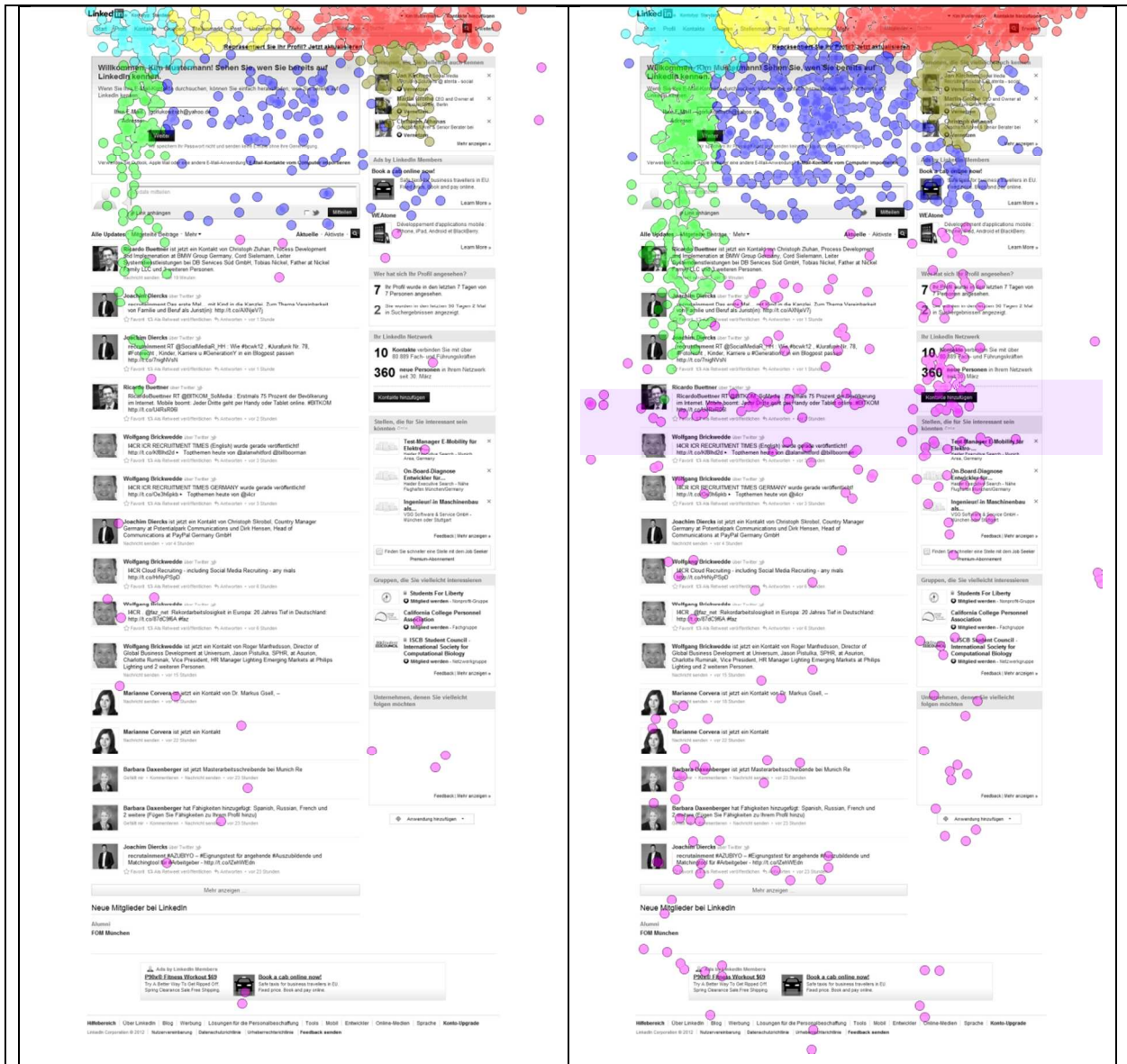
Figure 1. Behavioral IS usage patterns of experienced (left side) and inexperienced users (right side)

As it is our major research objective to objectively measure and to quantify IS usage behavior, we analyzed if the visually obvious behavioral IS usage patterns in Figure 1 can also be confirmed by conducting statistical analyses with the ROI distribution gathered through the Gaussian mixture model. Therefore, to support or reject our hypotheses we conducted a Chi²-test in order to analyze if the two groups observed behave significantly different both in general as well as within the individual ROIs. A Chi² value of 96.5 and consequently a highly significant p-value (see Table 3) reveal that experienced and inexperienced users are significantly different concerning their IS usage behavior, bringing support for hypothesis H1a. Proportionally viewed, experienced users have also significantly fewer views on the webpage in total. Furthermore, it also emphasizes that both groups have different usage patterns in their ROIs. For example experienced people tended to use the search functions more, whereas inexperienced people started the fulfillment of their task (asking for a job recommendation) from the menu point profiles and contacts on the toolbar more often than experienced people. Interestingly, as the people function (e.g., the only way to fulfill the task correctly) was frequented by both groups, it seemed that both groups regarded it as really useful but one requires experience in order to know how to use it, as more experienced

participants fulfilled the task correctly. While trying to learn to operate the system, inexperienced people had more fixations on friends' updates because they were exploring available functions on the website. Inexperienced users also had more fixations in average (experienced users =20.6 fixations < inexperienced users=26.0 fixations). Due to his behavioral patterns, we can also support H1b that experienced users have a more focused and efficient IS usage behavior than inexperienced users.

Table 3. Gaussian mixture model and Chi^2-test for experienced and inexperienced group								
experienced group								
ROI	1 (red)	2 (green)	3 (blue)	4 (magenta)	5 (cyan)	6 (yellow)	7 (brown)	total
number of fixations	276	95	104	26	97	53	89	740
percentage	0.373	0.128	0.141	0.035	0.131	0.072	0.120	1.000
inexperienced group								
ROI	1 (red)	2 (green)	3 (blue)	4 (magenta)	5 (cyan)	6 (yellow)	7 (brown)	total
number of fixations	568	297	363	249	504	137	199	2317
percentage	0.245	0.128	0.157	0.107	0.218	0.059	0.086	1.000
Analysis								
difference in percentage	**0.128**	0.000	-0.016	**-0.072**	**-0.086**	0.012	0.034	
average fixations	experienced users = 20.6 fixations				inexperienced users = 26.0 fixations			
Chi^2 value	96.5334							
p-value	< 0.001							

Results for the Effect of Pressure to Perform on Behavioral IS Usage Patterns

While the visual observation of the eye-tracking results for the experienced and inexperienced users revealed that experienced users predominately operate via the search function of the network, even if this is not the best or right way to fulfill the task, experienced users have fewer views and a stronger focus on just few regions of interest. Compared to the results for experienced and inexperienced users, the following Figure 2 visualizes that, alike experienced individuals, users under pressure to perform have the search function of the network as their preferred ROI (highlighted in red), while the non-pressured participants tended to view more the upper left corner leading the user to the starting page, his/her profile or those of already connected contacts. In terms of users' focus there are no visible differences between both groups, as both do more focus on the top third of the webpage. Statistically significant differences for the subjective visual patterns depicted in Figure 2 are listed in the following Table 4.
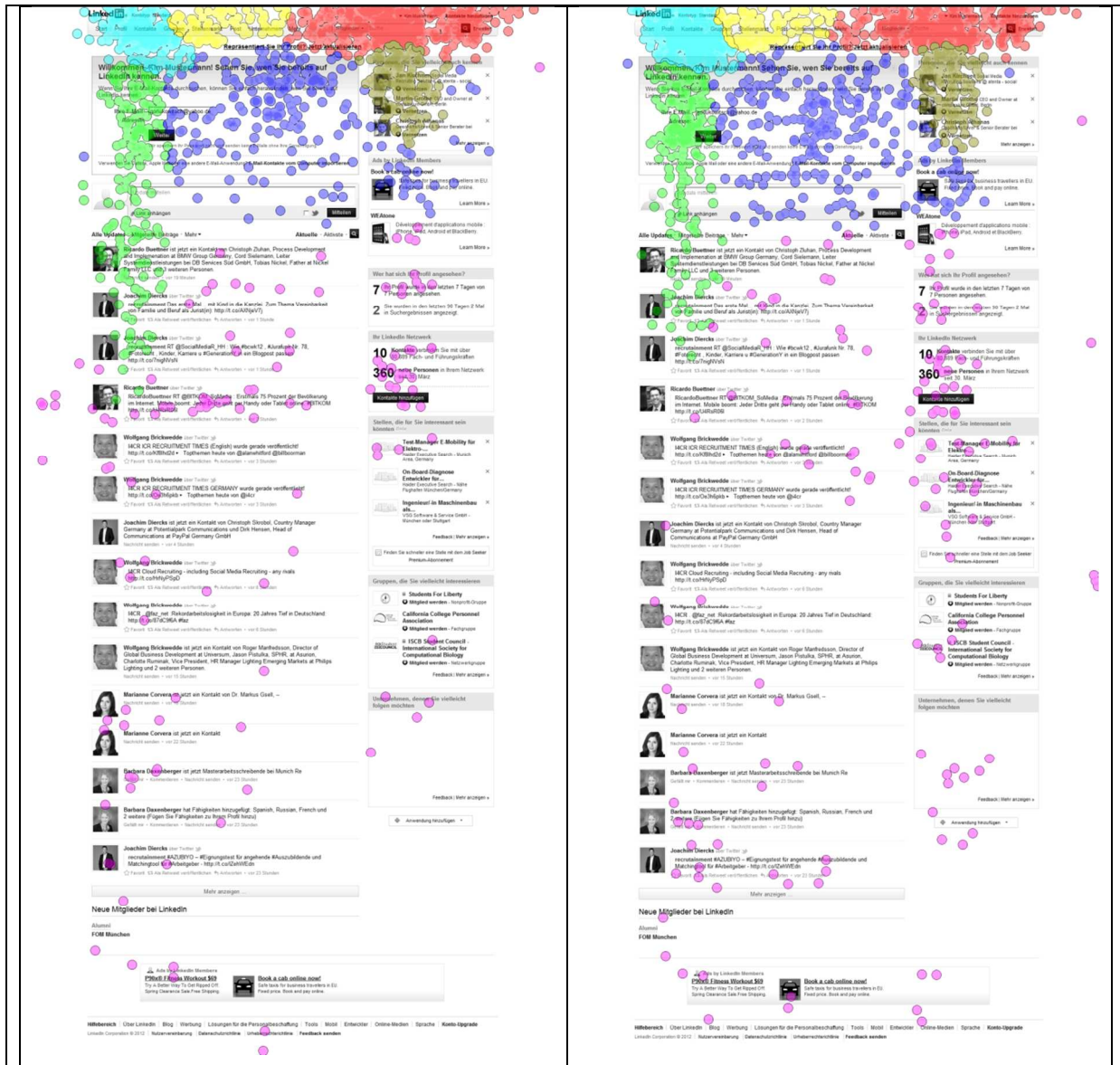
Figure 2. Behavioral IS usage patterns of users with pressure to perform (left side) and without pressure to perform (right side)

Referring to hypothesis H2a, we can summarize that also the groups of users, who are pressured to perform, and those, who are not, do significantly differ concerning their IS usage behavior. A Chi^2 value of 52.02 and a respective highly significant p-value for a significant difference between both groups supports H2a. While pressured individuals alike experienced users do also have fewer fixations than participants without pressure to perform, they also have similar usage patterns compared to pressured individuals. Both groups' of experienced and pressured people preferred to use the search functions (highlighted in red). Hence, this focused and efficient way of IS usage behavior and obviously similar strategic pattern compared to experienced users let us support H2b. Interestingly beside this similarities, we also managed to reveal a comparable IS usage behavior in some regions of interest for the non-pressured, as well as the inexperienced group. Non-pressured people tended to use the functions contacts and profiles on the tool bar more (highlighted in cyan), similar to inexperienced people. The results of the distribution according to the Gaussian mixture model, as well as the results for the Chi^2-test are represented in the following Table 4.

Table 4. Gaussian mixture model and Chi^2-test for pressured and non-pressured group								
pressured group								
ROI	1 (red)	2 (green)	3 (blue)	4 (magenta)	5 (cyan)	6 (blue)	7 (brown)	total
number of fixations	462	190	215	125	222	87	158	1459
percentage	0.317	0.130	0.147	0.086	0.152	0.060	0.108	1.000
non-pressured group								
ROI	1 (red)	2 (green)	3 (blue)	4 (magenta)	5 (cyan)	6 (blue)	7 (brown)	total
number of fixations	382	202	252	150	379	103	130	1598
percentage	0.239	0.126	0.158	0.094	0.237	0.064	0.081	1.000
Analysis								
difference in percentage	**0.078**	0.004	-0.010	-0.008	**-0.085**	-0.005	0.027	
average fixations	pressured users = 20.0 fixations			non-pressured users = 20.5 fixations				
Chi^2 value	52.0247							
p-value	< 0.001							

Discussion

We started our research with the objective to open the block box of individual IS usage behaviors. A literature review and meta-analysis by Williams et al. (2009) revealed that from more than 300 articles about IS use published in the top IS journals over the last twenty years, almost three quarters adopted either survey- or case study-based approaches; in contrast, less than two percent involved controlled experimental laboratory or field settings. Meanwhile, as discussed earlier, there are limitations of the both existing objective and subjective measures of IS usage. While it is suggested that objective measures outperformed subjective measures (Pentland 1989), there are a limited number of ways to obtain objective measures of IS usage. Against this backdrop, the emerging objective measures enabled by psychophysiological tools like eye-tracking device open up avenues to understand IS usage behavior in a more comprehensive and insightful manner (Dimoka 2010). More importantly, the statically method applied to analyze eye-tracking data has profoundly impacts on results that could be discovered.

Hence, to address the shortcomings in prior work on IS use and open the black box of IS usage, we conducted a laboratory experiment with 125 participants and captured their usage behavior by using eye-tracking technology. In contrast to several prior eye-tracking studies in the field of marketing or social psychology, which analyzed individual behavior just based on ROIs pre-defined by the researchers (e.g., Kroeber-Riel, 1979; Lohse, 1997; Dreze and Hussherr, 2003; Radach et al., 2003), or based on the subjective evaluation of individuals' fixation maps (e.g., heatmaps), we chose a data-driven approach that enables the researchers to keep an objective perspective when evaluating users' behavioral patterns. Specifically, we applied the Gaussian mixture model to discover users' actual ROIs and their frequency on view each of ROI. After the evaluation, we identified seven ROIs among the users. The results of Chi^2-tests revealed statistically significant behavioral differences across different user groups. Experienced users relied mostly (37 percent) on the search functions on the upper right side of the webpage to gather information for task fulfillment. In contrast, inexperienced users relied more on the first few buttons of the toolbar linking the user with his/her own profile and connected contacts in the network (highlighted

in cyan in Figure 1). Experienced users also tended to be more focused, as they had significantly fewer fixations than inexperienced users (20.6 fixations < 26.0 fixations); while experienced users focused primarily on the upper quarter of the webpage, including the toolbar and search functions, the inexperienced users viewed the other three quarters of the webpage containing irrelevant information to the task (such as contacts' status updates) more often than experienced users.

The results of the Chi²-tests also showed that pressured and non-pressured users were also significantly different in terms of their IS usage behavior. Similar to experienced users, pressured individuals were more focused since they only had one dominant ROI (i.e., the search functions – highlighted in red in Figure 1), and had fewer views on average (20.0 fixations < 20.5 fixations). Interestingly, when comparing experienced and pressured users, we found several similar behavioral patterns. Both groups had fewer fixations on average, and relied predominately on the search functions to look for information for task fulfillment. However, both groups chose the wrong starting point to fulfill their tasks successfully. To fulfill the task correctly, individuals needed to open the dropdown-menu of the profile or the contacts function on the toolbar (ROI 5 – highlighted in cyan). As this ROI was even more frequently used by inexperienced and non-pressured individuals, it remains an open question why experienced and pressured users relied more on the search function. Although, it is already known that pressured users may act less accurately due to the pressure to perform (Ahituv et al. 1998), it is counterintuitive why users with prior usage experience also choose this way to fulfill the task. A possible explanation might be some sort of "Google Bias": individuals prefer to use a search engine to look for information before elaborating the needed steps and procedures to fulfill a task.

Limitations and Further Research

Despite the controlled laboratory experiment and the use of objective eye-tracking data, this research has some limitations. First, lab experiments are criticized for their artificial settings as compared to real-world scenarios (Mook 1983). We addressed this issue by asking the participants to perform a task that is as realistic as possible to minimize the potential bias derived from artificial lab settings (Mook 1983). Another limitation is associated with the pressure of the participants. While some participants might have had a good day before the experiment, others might not have had a good one; pressure treatment may hence exert differential influences (Fisher et al. 2003; Marsden et al. 2006). Hence, we were not able to check for manipulation concerning experience and pressure. Future research might address this issue by replicating our experimental design by using questionnaires to check for potential manipulation of pressure and experience. Additionally, the average age of 29.6 years old of the sampled participants is more representative of the younger generation. Future research should assess whether our findings are replicable with older participants. Also individual differences in terms of participants' personality might influence their behavioral patterns during the laboratory experiment. On the one side neurotic individuals might be more affected by external treatments such as pressure to perform while on the other side extroverts or individuals, who are open to new experiences, could be less influenced in their IS usage behavioral patterns (Costa and McCrae 1992). It represents a promising avenue of future research to focus in more detail, how users are affected by their personality in the course of there is usage behavior. In addition to users' individual differences, researchers might also investigate the role and importance of the information system observed. As we just investigated users' behavioral patterns for the example of LinkedIn, future research can also analyze if the same behavioral patterns do also exist for the use of hedonic information systems (van der Heijden 2004). Finally, our observations on IS usage behavioral patterns just included the eye-fixations for one specific web page during the procedure for the fulfillment of one task. It seems to be an exciting further step in the direction of a deeper understanding of IS usage behavior, if researchers manage to reduce the complexity in observing eye-fixations and the related behavioral patterns for a complete task across different webpages.

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