Can e-Commerce Recommender Systems be More Popular with Online Shoppers if they are Mood-aware?

Fanjuan Shi[1,2] and Jean-Luc Marini[2]
[1]*Shanghai Unicore Technology of IOT Co., Ltd, Shanghai, China*
[2]*Search'XPR SAS, Clermont-Ferrand, France*

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Abstract: This paper presents the result of a controlled experiment studying how mood state can affect the usage of e-commerce recommender system. The authors develop a mood recognition tool to classify online shoppers into stressed or relaxed mood state unobtrusively. By analyzing their reactions to recommended products when surfing on an e-commerce website, the authors make two conclusions. Firstly, stress negatively impacts the usage of recommender system. Secondly, relaxed users are more receptive to recommendations. These findings suggest that mood recognition tool can help recommender systems find the "right time" to intervene. And mood-aware recommender systems can enhance marketer-consumer interaction.

1 INTRODUCTION

As the demand for user-centric web service rises, recognizing users' mood in real time becomes more and more important. Researchers have proposed various methods to detect users' mood. These methods include vocal signal analysis (Koolagudi and Rao, 2012), facial expression analysis (Fridlund, 2014), physiological indicators analysis (Silva et al., 2009), content-based semantic analysis (Baldoni et al., 2012), user input analysis (Khan et al., 2013), and hybrid solutions (Sebe et al., 2006). Mood-aware systems can not only analyze and identify users' mood in real time, but also take such context into account and propose correspondent service to users in the "right time", a moment when users are more receptive to these services. In practice, mood-aware systems have been integrated into video games (Ambinder, 2011), online learning systems (D'Mello et al., 2008; Mao and Li, 2009), productivity software (Bailey and Konstan, 2006) and other interactive computer systems (Kolakowska et al., 2013).

This paper focuses on applying mood recognition to e-commerce recommender systems, where few attention has been paid to users' real time mood states. In view of the European consumer privacy protection regulations, users' clickstream data was chosen as the data source for analysis. In Section II, we briefly review the main research topics and methods of mood recognition with computer users. Section III proposes our hypothesis, theoretical framework and a two-phased experiment approach. Section IV presents our experiment setting and result. Section V discusses about how to apply our findings to e-commerce and online marketing. Section VI concludes the paper and provides suggestions for future research.

This paper add value to the research of context-aware recommender systems in three aspects.

- It proposes a mood recognition tool which can recognize website users' mood state.
- It confirms that mood state affects users' reaction to the recommendations.
- It proves that recommendations of mood-aware system are more popular with online consumers.

These findings can help marketers to find new technics to satisfy online consumers and enhance the interaction between marketer and consumer.

2 RELATED WORKS

Recognizing users' mood is not a novel concept. The discussion about mood recognition is associated with four major aspects: How to define mood? Should mood be elicited? Which kinds of behavioral

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indicators to choose? How to associate behavioral indicators with mood?

2.1 Defining Mood

Mood can be referred as a specific emotion or state of mind (Lane and Terry, 2000). In general, researchers follow two different tracks to recognize users' mood.

In the first track, researchers encourage users to describe their mood state with their own mood taxonomy (Lee et al., 2012), and there is no limit on how many types of mood they can report (Epp et al., 2011). The advantage of this approach is that it helps to better understand individual level and complex mood states. However, aggregating users' feedbacks and making general conclusions can be challenging as taxonomy of mood are not standardized across users.

In the second track, the taxonomy of mood is predefined by researchers. Sometimes the taxonomy is exhaustive. One of the example is to define mood as "positive, neutral or negative" (Zimmermann et al., 2006; Khanna and Sasikumar, 2010). In other cases, researchers are interested in some specific moods such as sadness, fear, anger, surprise, or happiness (Lv et al., 2008). Consequently, their taxonomy of mood is non-exhaustive. As predefined taxonomy provides a standard to compare and classify the mood state of different users, it has been widely used by researchers who want to recognize and classify mood state of a group of users.

2.2 Eliciting Mood

Depending on the role of researchers in the experiment, the methods to study mood state can be classified into two groups.

In the first group, researchers play the role of observers. There is no stimulus to affect users' mood state. During the experiments, users' mood state are evaluated either by users themselves (Lee et al., 2012), or by trained assessors in an unobtrusively manner (Sottilare and Proctor, 2012). These methods allow researchers to associate moods with different kinds of behavioral features.

In the second group, various stimuli are used by researchers to elicit desired mood state. For example, requesting users to watch a video (Maehr, 2005; Zimmermann et al., 2006) or listen to a story (Lv et al., 2008) can provoke mood. Giving users challenging tasks (Vizer et al., 2009) or interrupting them when they are working (Epp et al., 2011) can cause stress. These methods help researchers verify whether certain behavioral features are universal across different users under a given mood state.

2.3 Selecting Behavioral Indicators

As mood might affect behavior, it is necessary to record users' behaviors for further analysis. Users' behavioral data is represented by a multi-dimension vector. Each dimension stands for a type of behavior indicator defined by the researchers. In the computer-assisted experiments, keystroke and mouse activities are commonly used by researchers as behavioral indicators (Zimmermann et al., 2003; Salmeron-Majadas et al., 2014).

Keystroke behavior indicators are associated with frequency, speed, and strength and idle time. Frequency indicators measures how often a key is used. Speed indicators measures how fast users type on the keyboard. They measure the duration of a keystroke, the duration between two keystrokes, or the average number of keystrokes in a given time interval. Strength measures how much pressure users put on the keyboard (Lv et al., 2008). Idle time measures the interval time between two input sequences. As moods might affect users' keystroke behavior, these behavioral indicators might help researchers to recognize users' mood state (Khanna and Sasikumar, 2010). For example, frequent usage of such keys as "Esc", "Alt+F4", "Backspace" and "Delete" might suggest that users are stressed; surge of keystroke strength might indicate that users are undergoing an extreme mood state.

Similar as keystrokes, mouse activity indicators might also be helpful to pinpoint users' mood states (Zimmermann et al., 2003; Lee et al. 2012). Mouse activity indicators are associated with click, scroll and travel behaviors, which can be captured by mouse tracking computer programs (Salmeron-Majadas et al., 2013). Frequency indicators measure how many clicks, scrolls and mouse moves are made by users, and magnitude indicators measure click speed, mouse traveling distance and web page movements.

Another source of behavioral indicator is clickstream data. Clickstream data are digital records of users' online behaviors in a chronological order (Montgomery et al., 2004). As the data collecting process is unobtrusive, detailed and automatic (Bucklin and Sismeiro, 2009), clickstream data are considered a reflection of users' interests (Chen and Su, 2013) and behavior (Olbrich and Holsing, 2011). With the help of clickstream data, researchers are able to reconstitute users' behavioral sequences and find out when and where behaviors are affected by mood states, which can potentially make mood recognition more accurate.

2.4 Recognizing Mood

Various data classification methods such as statistical analysis (Maehr, 2005), k-nearest neighbours algorithms (Lv et al., 2008), discriminant analysis (Vizer et al., 2009), support vector machine (Vizer et al., 2009), decision tree model (Epp et al., 2011), Bayesian network (Lee et al., 2012), and artificial neural networks model (Khanna et al., 2010) can be used to recognize users' mood state. Researchers selected methods based on the size of samples, the type of behavioral indicator (i.e. raw data or normalized data) and the number of moods to by detected, so as to achieve a higher accuracy.

3 HYPOTHESIS AND RESEARCH METHOD

3.1 Hypothesis

Our research is originated from a fundamental question: "Can e-commerce recommender systems be more popular if they are mood-aware?"

In the online shopping context, stress might be one of the most important mood to consider. The reasons are simple. Firstly, stress relief is one of the key motivations for shopping (Arnold and Reynolds, 2003). Secondly, online shoppers are often frustrated or confused by the excessive information displayed on an e-commerce website. Such information overload can create cognitive stress, which becomes a major source of stress (Vizer et al., 2009).

Research suggests that stress can prevent us from accepting external stimuli. Human brains can only focus on a limited number of things at a time (Horvitz et al., 2003). When we receive an external stimulus, our brain quickly evaluates its relevance to our current task, and decides whether we should ignore or attend to it. In a stressed mood state, our brain has less spare capacity to deal with external stimuli. In such circumstance, recommendations are more likely to be ignored without assessment.

E-commerce recommendations attract users' attention by interrupting their current task with a visual stimulus. Therefore, users' reaction to recommendations could be affected by stress. Based on this finding, the authors make two hypotheses:

- H1: stress has a negative impact on users' reaction to e-commerce recommendation
- H2: relaxed users are more receptive to the e-commerce recommendations.

3.2 Research Method

The authors partnered with a French e-commerce website (ECWP) to conduct the experiment, which consists of two stages: an offline stage to develop a mood recognition tool, and an online stage to test the tool with real users to find out how different mood states can affect users' reaction to online product recommendations (Figure 1).

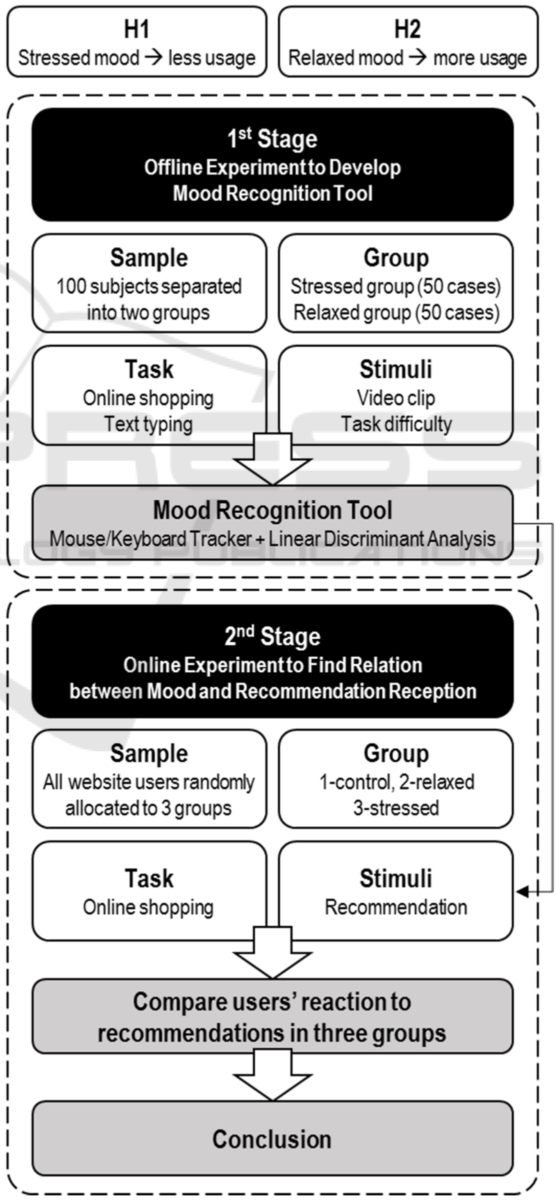

Figure 1: Research Framework.

In order to recognize the mood state of numerous website users unobtrusively and dynamically, it is necessary to develop an automatic mood recognition tool. Hence, an offline experiment was conducted in the first stage to allow the authors to develop a mood recognition model and train it with behavioral data with a group of users. Several conditioning technics were used in this stage.

Regarding participant selection, 2000 registered ECWP users were randomly selected as preliminary candidates. Then the list was trimmed down to 100 based on their demographic features, shopping experience with ECWP and availability. These participants were carefully selected so that they can represent ECWP users (Table 1).

Table 1: Composition of ECWP users and the experiment participants.

Gender	**Female**	**Male**			
ECWP users	53%	47%			
Experiment group	50%	50%			
Age (years old)	**≤25**	**26-35**	**36-50**	**51-60**	**>60**
ECWP users	17%	34%	26%	19%	4%
Experiment group	20%	30%	30%	15%	5%
Total Spending (€/year)	**≤25**	**26-50**	**51-100**	**101-200**	**>200**
ECWP users	71%	25%	2%	1%	1%
Experiment group	63%	29%	4%	3%	1%
Shopping Frequency (time/year)	**0**	**1-2**	**3-5**	**>5**	
ECWP users	63%	28%	7%	2%	
Experiment group	52%	31%	10%	7%	

When designing the offline experiment, the authors refer to the methods used by Zimmermann et al. (2006) and Vizer et al. (2009). To simulate ECWP user traffic flow, experiment sessions were scheduled at different time of the day. Participants were split into two groups – the first one was relaxed and the second one was stressed. In each group, participants began by watching a video, and then completed a series of online shopping tasks. Relaxing and stressful video clips were used to elicit mood, and task difficulty was adjusted based on the type of group (i.e. relaxed or stressed) to reinforce the desired mood. In the relaxing group, participants were requested to assess five digital cameras (of similar price) displayed on ECW, choose one model to offer to their best friend and prepare a 300-word summary in word processor to justify their choice. They could ask questions before starting the task, and there was no time limit to complete the task. In the stressed group however, participants were requested to choose a photocopier for their organization. They must evaluate five photocopiers of similar price provided by ECWP, choose the most suitable model and make a formal purchase application to their supervisor in word processor to justify why the selected model was better than others. Participants were told that the task must be finished in 15 minutes, and a countdown clock was provided as a reminder of the remaining time.

Before starting the tasks, a brief tutorial session was conducted in both groups to introduce ECWP website and the task to be completed. Therefore, the lack of shopping experience with ECWP would not be a cause of stress in the experiment. Consequently, the stress of the stressed group comes from three sources: 1) time stress: trial experiment indicated that 15 minutes was barely enough to complete the task; 2) cognitive stress: preparing formal purchase application requires participants to be more prudent and attentive in their work; 3) psychological stress: the countdown clock further intensified the stress.

Participants' behavioral data were collected by web cookie and java-based trackers. The data were processed by linear discriminant analysis method to construct and validate the mood recognition tool.

Once the mood recognition tool is ready, it was used in the second stage of the experiment to determine when to send recommendations to users. The second stage took two weeks, and participants were all the ECWP users. When users started a session on ECWP website, they were allocated randomly, equally and unobtrusively into three groups. Users in Group A received recommendation as normal. The mood state of users in Group B were assessed by the mood recognition tool in real time, based mouse and keyboard trackers. Users received recommendation only when they were considered stressed. Using the same method as in Group B, users in Group C received recommendation only when they were considered relaxed. Their reactions to recommended items were analyzed by statistical approach to verify if mood can affect their reaction to online recommendations.

The recommender system of ECWP uses a collaborative filtering algorithm, which assumes that users who have similar tastes will rate things similarly. Sometimes the recommendations are directly related to users' current interest. Sometimes the recommended items can be very different from the product being viewed by users. A click on the recommended item is defined as positive reaction to the recommendation. Similarly, a close activity is defined as a negative reaction.

4 EXPERIMENT RESULT

4.1 Analysis and Result of the First Stage

The authors use the linear discriminant analysis (LDA) method to develop the mood recognition function. During the experiment, a dozen of mouse activity, keystroke, and clickstream data were collected by trackers and cookies. These data include session time, frequency of keyboard usage (defined by a five second delay between two keystrokes), frequency of keystroke, frequency of mouse click, frequency of mouse movement, frequency of mouse scrolling, traveling distance of mouse, timestamp for web page open, and timestamp for web page close. Then, these observations were converted into comparable variables.

Among all the 100 cases collected by the experiment, 53 case were randomly selected as modeling cases (23 stressed and 30 relaxed), and 47 case were used as validating cases (27 stressed and 20 relaxed). The predictors of the model were selected based on a few considerations. Firstly, with-in groups correlation matrix was used to minimize collinear predictors in the model. Secondly, one-way ANOVA test was conducted to confirm that predictors are significantly different among groups. Thirdly, the model's discriminatory ability must be acceptable, meaning that the prediction accuracy must be acceptable not only for the modeling cases, but also for the validating cases. Based on these criteria, four variables were selected (Table 2).

Table 2: List of predictors.

Predictor	Definition (measurement)
mvt_spd	Average distance of each mouse move (pixel/move)
sty_pg	Average time spent stay with a page (second/page)
clc_min	Average number of mouse click per minute (click/minute)
dly_stk	Average time between depressing and releasing a key (millisecond)

In the modeling cases, there were less stressed users than relaxed users. For the authors, the main objective of the discriminant function is to recognize "stressed" users. Therefore, prior probabilities of stressed and relaxed mood state were computed according to the group sizes, so that the model can be more conservative. The syntax to crate discriminant model in SPSS is:

```
  DISCRIMINANT
     /GROUPS=Group(0 1)
     /VARIABLES=mvt_spd time_pg clc_min
dly_stk
     /SELECT=model(1)
     /ANALYSIS ALL
     /SAVE=CLASS SCORES PROBS
     /PRIORS SIZE
     /STATISTICS=MEAN STDDEV UNIVF BOXM
COEFF RAW CORR COV TABLE CROSSVALID
     /CLASSIFY=NONMISSING POOLED.
```

Based on 53 selected cases, the discriminant model is:

y = 0.022dl_kystr – 0.046time_pg + 0.414clic_min + 0.001mvt_speed – 6.17

	Function
	1
dly_stk	.543
sty_pg	-.474
clc_min	.473
mvt_spd	.360

Figure 2: Structure matrix.

One-way ANOVA tests indicates that the null hypothesis can be rejected at 2% level. The within-groups correlation matrix shows that the largest correlation between predictors is 0.241 (correlation between mvt_spd and clc_min). The p-value of Box's test of equality of covariance matrices is 0.127. Wilk's lambda of the canonical discriminant function is 0.509. And p-value is 0.000, suggesting that the discriminant function is effective. The structure matrix (Figure 2) shows that dly_stk has the strongest discriminatory ability, followed by sty_pg, clc_min and mvt_spd.

Classification result indicates that the 83% of the modeling cases and 87% of the testing cases can be correctly classified, suggesting that the model is stable and reliable.

				Predicted Group Membership		
Group				Stressed	Relaxed	Total
Modeling Cases	Original	Count	Stressed	17	6	23
			Relaxed	3	27	30
		%	Stressed	73.9	26.1	100.0
			Relaxed	10.0	90.0	100.0
	Cross-validated	Count	Stressed	16	7	23
			Relaxed	5	25	30
		%	Stressed	69.6	30.4	100.0
			Relaxed	16.7	83.3	100.0
Testing Cases	Original	Count	Stressed	22	5	27
			Relaxed	1	19	20
		%	Stressed	81.5	18.5	100.0
			Relaxed	5.0	95.0	100.0

Figure 3: Classification results.

4.2 Result of the Second Stage

The dataset of the two-week live experiment consists of 52,896 sample users. The mood recognition tool finds that 27% of them experienced stress during a session. The statistics of the different groups are highlighted in Table 3.

Table 3: Experiment result of the second stage.

RESULT 2ND STAGE	Group A	Group B Stressed	Group C Relaxed
Sample Users	17,632	17,632	17,632
Recommendations	88,215	24,271	64,399
Stressed mood (%)	-	27.17%	26.51%
Relaxed mood (%)	-	72.83%	73.49%
Recommendation Click	1,411	199	1,256
Recommendation Close	2,602	796	1,848
Time to click (second)	13.55	16.12	11.05
Time to close (second)	3.48	3.17	3.79

Click through rate and close rate are used to measure the performance of recommender system in different mood state (Figure 4). Click through rate measures how many displayed recommendations end up being clicked by ECWP users. It confirms that recommendations were more welcomed when users were in a relaxed mood, and users in a stressed mood showed little interest to recommendations. Close rate measures how often ECWP users reject a recommendation by removing it from the screen. It indicates that stressed users were more likely to reject recommendations actively than relaxed users.

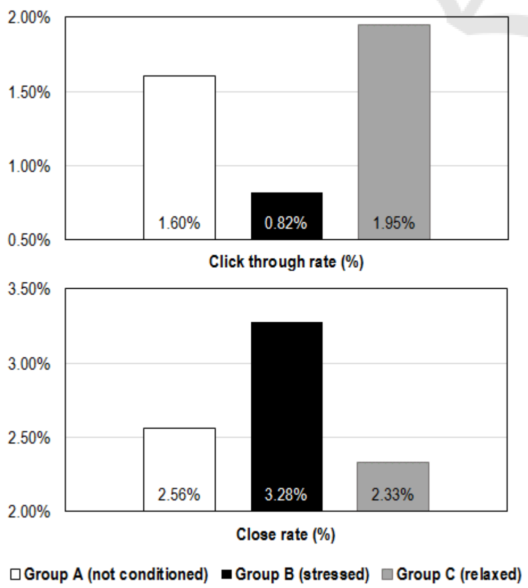

Figure 4: Recommendation click through and close rate by experiment group.

Behavioral data indicate that stress can affect users' time to react (Table 3). Compared with relaxed users, it took longer for stressed users to click on recommended items. And stressed users rejected recommendations more quickly than relaxed users. Based on these findings, we can conclude that stress negatively affect ECWP users' reaction to online recommendations. In order to enhance the usage of recommender system, recommendations should be sent to users when they are less stressed.

5 DISCUSSION

Our findings can bring to online marketers several key insights.

Firstly, online consumers are not always relaxed. In some cases (e.g. 27% in ECWP), they can be stressed. Taking care of their affective state might help online marketers to reduce website abandonment rate, increase deal conversion rate and enhance consumer satisfaction. By deploying real time mood recognition tool, online marketers can know when to take necessary measures to relax consumers and then help them to find what they want. Such measure include changing the color of website layout, propose a chat through instant messenger and so on.

Secondly, the "right time" plays a very important role in a successful recommendation (Fischer, 2012). According to our findings, the right time for recommendation is when users are in the relaxed mood. For push-based recommender systems, mood recognition tools can judge when to stop pushing recommendations so as not to disturb the stressed consumers. For pull-based online marketing systems, mood recognition tool can help to manage the cognitive load (i.e. the content to display) to consumers.

Our research method has some limitations. Firstly, the mood recognition tool was developed based on the behavioral data of ECWP users. Therefore, the tool might not be applicable to other e-commerce websites. Secondly, due to the experiment budget and time constraints, the authors used only one machine learning method (i.e. linear discriminant analysis) to develop the model. The authors believe that the prediction accuracy of mood recognition tool might be further enhanced, if other methods (e.g. artificial neural networks) can be tested on a larger data set. In the future research, the authors will try to incorporate these considerations into consideration.

In order to apply our method to the e-commerce practice, we suggest online merchants pay attention to two aspects.

The first is that an e-commerce website must obtain users' consent before collecting their online behavioral data unobtrusively. In our experiment, participants were requested to sign a waiver before being accepted. In practice, necessary modification must be made to the website's disclaimer, so that consumers are given the right to accept or refuse to be monitored.

The second is that the effectiveness of the mood recognition tool should be reviewed from time to time to maintain its predictive power. Users' mood can be affected by many different contextual factors such as season, weather, health, motivation, or environment. To determine the effectiveness of the mood recognition tool, e-commerce websites can pop up an inquiry of users' current mood state on the user interface, and compare users' response with the prediction result. If the classification accuracy is low (e.g. less than 80%), the e-commerce website can use the collected data to rectify the mood recognition tool.

6 CONCLUSIONS

This paper presents a method to incorporate mood recognition into online recommendation. Experiment shows that quite an amount of online consumers were in a stressed mood, and recommendations were more popular with relaxed users than stressed users. Such findings can be used by recommender system developers and online marketers to improve user experience and enhance consumer satisfaction with e-commerce websites.

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