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# 웹환경에서 시계열 예측의 정확성제고를 위한 감성조건과 뇌파특징 추출에 관한 연구

# A Study on Emotion and EEG to Improve the Accuracy of Judgmental Time Series Forecasting in a Web-based Computer Task

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요 약 감성은 의사결정에 많은 영향을 미침에도 불구하고, 시계열예측에 있어서의 연구는 매우 적은 편이다. 본 연구는 감성이 시계열 예측에 미치는 영향을 시계열정보의 형태 (그래프, 계절성)와 더불어 살펴보았다. 감성은 피험자로 하여금 인터넷시험을 보게 하고 즉시 그 결과를 알려줌으로 유발하였다. 시험결과가 좋은 피험자에게는 상금을 주어서 그 효과를 극대화하도록 하였다. 본 연구는 팩토리얼로 설계되었으며, 86명의 학생이 인터넷에서 운용되는 실험프로그램을 직접 사용하였다. 그 결과 감성은 그 자체로는 효과가 없었지만, 정보가 주어진 형태와 관련되어 그 효과가 나타났다는 점이 매우 흥미롭다. 특히 좋은 감성이 유발된 경우, 계절성을 테이블형태로 (그래프에서 잘 표현될 수 있다는 점에도 불구하고) 더욱 정확하게 처리하는 경향이 있었다. 또한 피험자의 뇌파를 분석한 결과 전두엽의 베타파가 정확성에 많은 기여를 하는 것으로 나타났다.

## 1. Introduction

Despite the prevalence of various sound statistical tools and theories, managers often rely more on their gut feeling when it comes to making prediction. Therefore, most firms appear to take a simple judgmental approach to sales forecasting (Dalrymple, 1987). Forecasting is a complicated task and the exercise of proper judgment requires much cognitive effort. Given this, it is quite likely that forecasters may simplify the task so that it can be easily managed (Payne, 1976). Such task simplifications may, however, lead to judgmental bias (Hogarth & Makridakis, 1981). Psychologists and decision support systems (DSS) practitioners have argued that some level of guidance is therefore essential in tasks where people rely on their judgment to make managerial decisions concerning future trends (Hogarth & Makridakis, 1981). Guidance in forecasting may include (1) the provision of accurate statistical forecasts and causal information, (2) the graphical presentation of time series, (3) feedback of past forecasting errors and (4) some warnings of likely judgmental biases (Lim, 1994). While these factors relate to the cognitive process involved in decision making, a number of recent studies indicate that emotional factors may also play a role, particularly at different phases of decision making. For

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example, it has been reported that emotional factors affect the way decision makers utilize decision aids (Luce et al., 1997) and may affect the selection of decision strategies for a task (Isen & Means, 1983). This suggests that emotion is a factor that may have an important influence on the accuracy of decision outcomes (Stone & Kadous, 1997) and thus it should not be overlooked in research. However, to date there has been little empirical investigation into the effect of emotion, specifically on judgmental forecasting.

This study aims to explore how emotion and information modality may affect the accuracy of making time series forecasts. We shall also look at some physiological measures in relation to the task of judgmental forecasting. Physiological measures may provide some insights into the mind-body relationship and may shed some lights on related cognitive processes. This study will be valuable to the designers of decision support systems who want to incorporate an emotion factor and biofeedback into more effective systems of aiding forecasters and decision makers. The research questions to be examined in this study are as follows:

- Does emotion affect the accuracy of time series forecasting?
- Does emotion cause people to use tabular and graphical information differently?
- Does emotion influence the way people learn?
- Do physiological recordings provide insights into forecasting accuracy?

## 2. Literature Review

**Effect of emotion**

Empirical evidence has shown that the way emotion plays a role in decision making varies according to valance of the emotion. For example, Goldberg and Gorn (1987) found that commercials were more effective when embedded within happy programs than within sad programs. On the other hand, when viewers liked watching the sad programs, advertisements embedded within them were just as effective as the ones embedded in positive-emotion programs (Murry et al., 1992). A number of studies have also suggested that emotion affects decision making styles and this would certainly affect decision outcomes. People tend to be more intuitive in their judgment when in a happy mood and more analytical when in a sad mood (Schwarz, 1990). Indeed, it has been reported that increasing task-related negative affect appeared to increase use of scanning strategies, which increased choice accuracy in easy tasks but impaired it in difficult ones (Stone & Kadous, 1997). Isen (1983) explained such results more directly by addressing the role of emotion in the selection of decision strategies. Isen argued that when a happy mood was induced, people tended to simplify the problem space and employ shortcuts in their decision making (i.e., Elimination-By-Aspects, Payne, 1976).

To summarize, first, it seems that different types of emotion can lead to the selection of different strategies for decision making and these in turn can result in different decision outcomes. Second, these strategies may be related to the use of cognitive effort in order to maintain or change their current emotional state. This tendency may influence decision accuracy, however there has been very limited research that addresses this issue. As a basis for this initial investigation, we propose two non-directional hypotheses. Non-directional hypotheses are proposed because of the dearth empirical studies conducted specifically in this area.

The first hypothesis is that there will be a difference in forecasting accuracy between the good emotion and the bad emotion groups. The second hypothesis concerns the display format of the presentation of the information. In the experiment two types of presentation format will be employed. graphical and tabular. Chernoff (1973) has demonstrated that using a graphical format to represent aspects of the data is a powerful way to depict complex relationships between multiple variables. That is, visual information rapidly indicates similarities, differences and trends in the data that may otherwise be obscure. However, it is also possible that graphical representation may accentuate a tendency to over-simplify complex functions and so entrench processing biases thus leading to consistent poor performance. The second hypothesis is that there will be a difference in forecasting accuracy between the graph and the table groups.

**Other variables**

The effect of information format may potentially interact with the predictability or regularity of data on which a forecast is based, which is also related to the difficulty of the judgmental task. In this regard, the research will include the variable of a seasonality to manipulate the extent of regularity within the data on which predictions are based. Previous research by Lim and OConnor has shown that people could learn the prediction task the number of trials. It is plausible that this variable will also interact with the two main variables (see above) and so the research will include more than one trial in order to determine whether this is the case.

## 3. Experiment 1

### 3.1. Research Method

**Participants**

86 under- and postgraduate students participated in the experiment taking a role of surrogate managers. Most participants were students at the School of Information Technology and Telecommunications of Sangmyung University. They took part in the experiment as part of a lab class, however they were informed that those who ranked high in terms of forecast accuracy would be given extra monetary reward (although at the end all of them were actually provided with a $5 coupon for their participation).

**Research Design**

The research was conducted as a 2 (good vs. bad emotion) x 2 (graph vs. table display) x 2 (non-seasonal vs. seasonal series) x 4 (number of trials) factorial design. The first factor was (1) positive and (2) negative emotion and was manipulated by providing positive feedback and a coupon to induce a positive emotion, or negative feedback and no coupon for negative emotion. The second factor was an information format and was manipulated by the way that time series was presented either in a graph or in a table. The third factor was the extent of seasonality contained in the time series. The last factor, trials, was a within subject variable as it accounted for the rounds of time series that were given for the participants to forecast. That is, each participant was presented with four rounds of time series. So their performance cross from round one to four can be contrasted.

**Tasks**

Ten time series were used in this experiment (these were taken from M-Competition, Makridakis et al., 1982). This set of time series has been successfully used in a series of earlier experiments (Lim & OConnor, 1996). The task was worded as a computer sales scenario, so that it would attract students interest. Participants were asked to imagine themselves as managers of a computer company and to project sales for six-periods ahead from a given time series. This resulted in a total of 96 forecasts produced by each subject (four time series x four rolls x six-period ahead forecasts). The experimental task took about less than an hour to complete.

**Instrument**

The instrument used in this study was programmed in Tcl/Tk by the first author to run on Web. It was designed to be very user friendly. The sequence of tasks to be taken throughout the experiment were all displayed on the top of the screen and sequentially highlighted for the subjects to follow. The program presented a large text area so that the participants could read the experimental instructions for each step (see Figure 1)

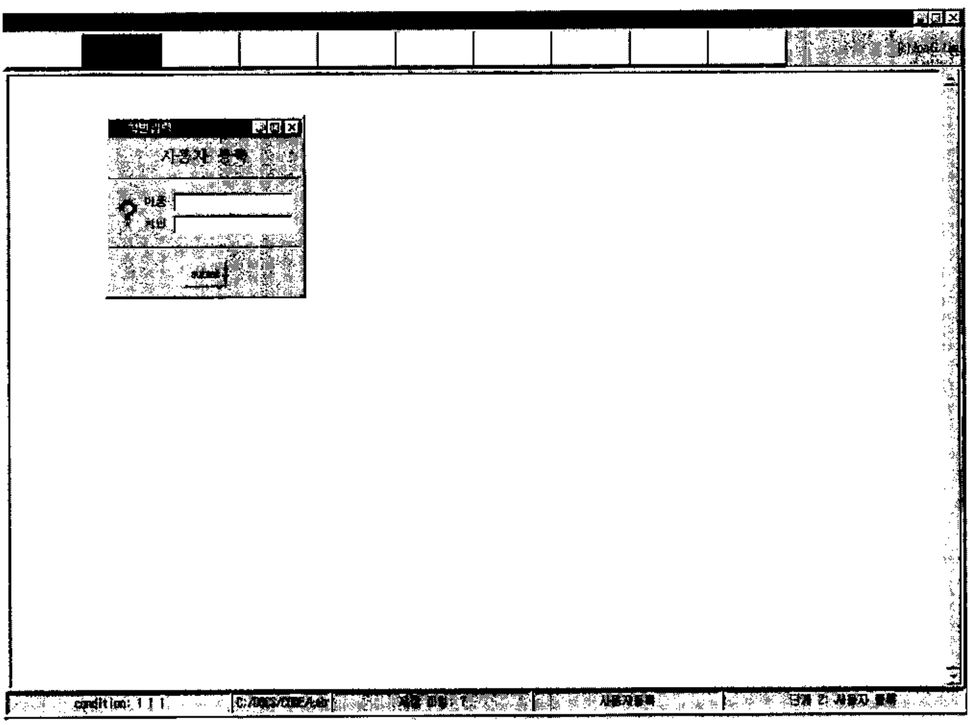

Figure 1 : Initial Screen of Lab Software

**Independent Variables**

As mentioned earlier, there were four independent variables controlled as follows:

- Emotion: It was manipulated by feedback and monetary incentives in relation to the exam results. It should be noted, however, that this manipulation was not related to the time series task, but the earlier exam. That is, those in the good (or bad) emotion condition were informed of good (or bad) marks and provided with monetary incentives depending on their assigned group. For this manipulation work well, we displayed the question numbers that the participants got wrong along with the marks. Both groups were asked to perform as reliably as possible during the lab, since they were told that overall performance would be taken into course grading.
- User interface: Time series data were differently presented depending upon the condition that the participants were randomly allocated to. Time series was either graphically displayed (Graph condition) or displayed in a tabular format (Table condition). Caution was paid to that the amount of information was designed not to be different one from the other condition (see Figure 2 & Figure 3)
- Seasonality : There were two types of time series one being non-seasonal, the other being seasonal series as used in Lim and OConnor (1996).
- Trial: The number of rounds of each time series they performed (ranging from one to four).

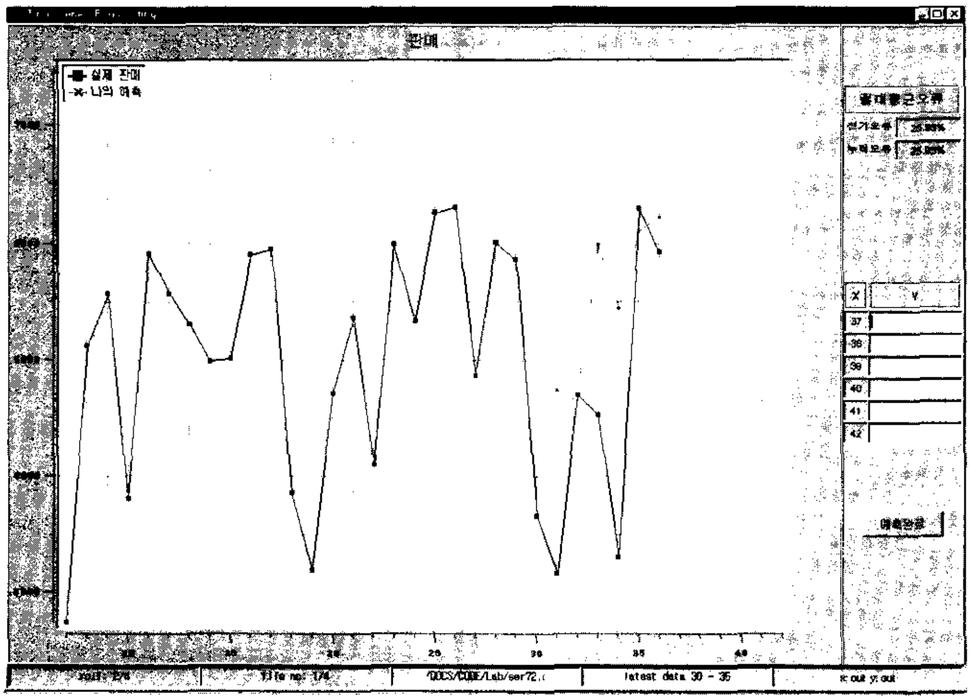


Figure 2 : Graphical display of Time Series

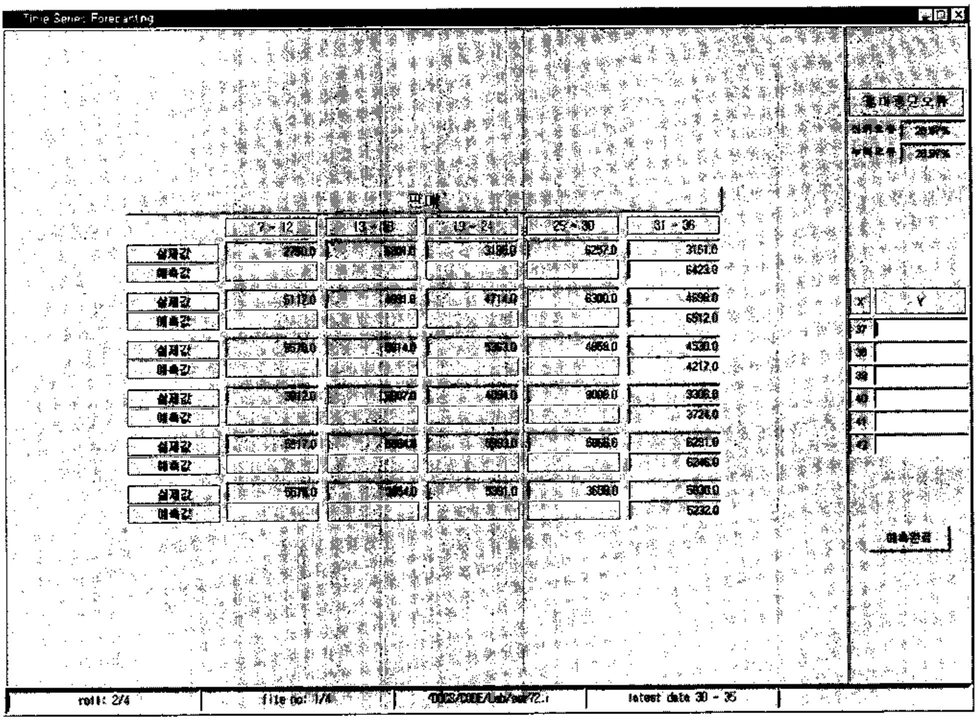


Figure 3 : Taular Display of Time Series

**Dependent Variables**

Three dependent variables were measured as follows:

- Accuracy: MAPE (Mean Absolute Percentage Error) was adopted because of its wide-spread academic use (Carbone & Amstrong, 1982) and its robustness (Armstrong & Collopy, 1992). It measures the extent of deviation of subjects forecasts from the actual values (optimal criterion).
- Subjective measures: Subjects were asked to report their feeling on a 5-point Likert scale. It should be noted that it was a subjective indicator of their emotion (this study measured two-dimensional emotion as defined in Larson and Diener (1992)) e.g., how good or bad emotion they experienced in relation to the experimental manipulation of emotion. Thus, there shall be some deviation in the subjectively reported ratings among the subjects in the same condition.

**Procedure**

All participants were seated and briefed in general about the task, the instrument and the types of incentives. These instructions were also displayed to the participants as the task proceeded. Then they were randomly allocated to the experimental conditions. Subjective emotion was evaluated to determine if there was any difference in emotion between groups at the beginning. This was followed by the emotion manipulation. The participants were asked to take an exam on the lecture subject (i.e., Javascript). On completing the exam, they were asked to move to the next room where refreshments were provided. When all students finished the exam and thus the room was empty, we placed a coupon underneath a mouse pad only for those in the good emotion condition. The participants were asked to come back to the exam room and open a feedback dialog box giving their exam results; they were told that there were coupons underneath mouse pads for those who ranked relatively high. They were asked not to share their marks with neighbors and keep quietly carrying on with the rest of the experiment. They were then asked to report their subjective emotion. After this, the time series was displayed either in graphical form or in tabular form depending on the condition and the participants were asked to project 6-period ahead forecasts for the given time series. This task of judgmental forecasting was repeated for four times with four different time series. After this task, a set of questions was given to the participants to indicate their feelings and attitudes. This experiment was performed in one sitting.

### Analysis Methodology

There were initially 55 participants in the experiment of whom 54.6% (30) reported changes in their subjective emotion as intended in this study. So, few days later we ran an additional lab with 31 subjects. Non-parametric analyses with the Mann-Whitney U test did not reveal any significant differences in MAPE due to date (24.96 vs. 25.89) ($z=-1.348$, $p$=ns). Prior to any analysis, Cooks distance was run to remove any outlier contained in MAPE data. Experimental data were also visually scanned for any artefact. An outlier was found and thus, removed from further analysis (MAPE=669.97). As seen in Tabel 1, there were total of 85 participants with the range of between 16 and 26 for each condition. Not all subjects reported their emotion as intended in this study. 2 (emotion) x 2 (information display) x 2 (seasonality) x 4 (trials) ANOVAs were computed. To test the effect of emotion, along with ANOVAs correlation analyses were also performed on subjective ratings of emotion obtained from questionnaires

Tabel 1 : The number of participants in the experiment

| | Table | Graph | Total |
|---|---|---|---|
| Bad Emotion | 16(1536) | 23(2208) | 39(3744) |
| Good Emotion | 20(1920) | 26(2496) | 46(4416) |
| Total | 36(3456) | 49(4704) | 85(8160) |

( ) : the number of cases

### 3.2 Results

#### Manipulation Check

All participants were asked to report their subjective emotion (how good or bad they were feeling) prior to starting the lab session. There was no difference in subjectively reported emotion between the bad and the good emotion group with all subjects included (2.97 vs. 3.02) ($z=-1.895$, $p=0.58$). Remember they were then exposed to emotional control. Depending upon the way subjective emotion was changed with emotional control of this study, the subjects were divided into two groups. The controlled group included those who reported appropriate changes in their subjective emotion as intended in this study. On the other hand, the uncontrolled group consisted of those who reported no change or in the opposite direction of their emotion. That is, the uncontrolled group represented those in the good emotion condition who received treatment to let them feel more pleasant reported rather deteriorated pleasant feelings and vice versa. Table 2 shows that those who indicated the opposite or no-change to the manipulation were about half the subjects. It may be due to that emotion control tended to be ineffective for those who initially indicated comparatively good (or bad) feeling in the relevant groups. Given that the emotion was controlled in a way to let the good (or bad) emotion group to be better (worse) than they had been, our analysis focused on those who reported changes in their subjective emotion as manipulated in this study. Those for whom the emotion manipulation was ineffective were used as a control group and we would present the results, if needed, between these groups (all subjects vs. only those subjects whose emotion was controlled). Note that the bad emotion group appeared to report higher level of stress than fatigue on a 5-point Likert stress-fatigue scale. On the other hand, the good emotion group did not indicate any of biased stress-fatigue feelings. The Mann-Whitney U test showed that the controlled group was not significantly different from the uncontrolled one in MAPE (24.70 vs 25.81) (z=0.617) and emotion as well.

Tabel 2 : The number of subjectis by the emotion was controlled

| | | Not Controlled | | Controlled | Total |
|---|---|---|---|---|---|
| | | Abnormal | no Change | | |
| bad | Table | 2(192) | 4(384) | 10(960) | 16(1536) |
| | Graph | 2(192) | 11(1056) | 10(960) | 23(2208) |
| good | Table | 6(576) | 4(384) | 10(960) | 20(1920) |
| | Graph | 1(96) | 15(1440) | 10(960) | 26(2496) |
| | | 11(1056) | 34(3264) | 40(3840) | 85(8160) |

( ) : the number of cases

Table 3: ANOVA on MAPE

| | | df | F | Sig. |
|---|---|---|---|---|
| Main Effects | A | 1 | 3.630 | .057 |
| | B | 1 | 22.831 | .000*** |
| | C | 1 | 81.396 | .000*** |
| | D | 3 | 2.915 | .033* |
| 2-way Interactions | A×B | 1 | 2.701 | .100 |
| | A×C | 1 | .362 | .548 |
| | A×D | 3 | 2.069 | .102 |
| | B×C | 1 | 14.365 | .000*** |
| | B×D | 3 | 1.603 | .187 |
| | C×D | 3 | 4.008 | .007** |
| 3-way Interactions | A×B×C | 1 | 4.998 | .025* |
| | A×B×D | 3 | .561 | .641 |
| | A×C×D | 3 | 1.223 | .300 |
| | B×C×D | 3 | 1.614 | .184 |
| 4-way Interactions | A×B×C×D | 3 | .466 | .706 |

A : Emotion (good vs. bad), B : Display (graph vs. table), C:Seasonality (seasonal vs. nonseasonal), D : Trial(number of trials)

**$H_1$ : Emotion Effect**

It was hypothesized that there will be a difference in forecasting accuracy between the good and the bad emotion groups. To ensure the effect of emotion on performance, we compared the differences in emotion between emotion groups after emotion control. As seen in Table 4, the good emotion group reported significantly more pleasant feeling than did the bad emotion group (4.10 vs. 1.85) ($p<.001$). Empirical evidence from psychology suggests that people experiencing a negative emotional state tend to be more analytic (Schwarz, 1990). Given this, we expected that the bad emotion group would benefit from this analytical tendency and perform better than the good emotion group. To the contrary, the results of ANOVA did not bear out such an effect there was no significant difference in MAPE between two groups (25.73 vs. 23.85). (p=ns). Putting all subjects into analysis, non-parametric analyses with the Mann-Whitney U test fail to yield any significant differences between two groups (25.50 vs. 25.04) (z=-1.806, p=ns). In the light fact that subjective emotion was measured, correlation analysis was performed to test the hypothesis. Collaborating the above results, the accuracy was not significantly correlated with the subjectively reported emotion with all subjects included (r=.006, p=ns). One may assume that emotion may bear out well over the earlier rolls of judgmental forecasting and this was not found (25.04 vs. 25.30). Thus, the first null hypothesis was rejected.

Table 4 : Average of reported subjective emotion by the way emotion was controlled

| Goodness of Emotion | Uncontrolled | | Controlled | | all | |
|---|---|---|---|---|---|---|
| | Bad | Good | bad | Good | bad | Good |
| Before emotion control | 3.32 | 2.65 | 2.65 | 3.50 | 2.97 | 3.02 |
| After emotion control | 2.84 | 2.96 | 4.10 | 1.85 | 3.49 | 2.48 |
| After the lab | 3.00 | 3.04 | 3.05 | 3.10 | 3.03 | 3.07 |
| No. of cases | 1824 | 2496 | 1920 | 1920 | 3744 | 4416 |

(1 : good vs 5:bad)

Table 5 : MAPE Means for Emotion x Display Conditions

| | table | graph | Average |
|---|---|---|---|
| Bad emotion | 24.03 | 27.42 | 25.73 |
| Good emotion | 20.20 | 27.14 | 23.67 |
| Average | 22.12 | 27.28 | 24.70 |

**$H_2$: Display Effect**

We expected that graph could reveal trends and patterns contained in time series and thus, people with time series presented in graphs would produce more accurate forecasts than in tables. It was, however, found that tabular display led to a higher accuracy than the graphical display of time series data (22.12 vs. 27.28) (F=21.831, p<.005). It may be due to that the good emotion group appeared to outperform the bad one, not significant though, when time series data were presented in graphical format, presented the good emotion group. It may be due to the fact that subject with tabular display tended significantly more time than those with graphical display (3669 vs. 2683). Thus, the second hypothesis was rejected.

Table 6 : MAPE Means for Emotion x Display x Sesonality Conditions

| | | Table | Graph | Average |
|---|---|---|---|---|
| Bad emoton | Non-seasonal | 19.68 | 21.38 | 20.53 |
| Bad emotion | seasonal | 28.39 | 33.46 | 30.93 |
| Good emotion | Non-seasonal | 18.91 | 19.33 | 19.12 |
| | seasonal | 21.49 | 34.94 | 28.22 |
| Average | | 22.12 | 27.28 | 24.81 |

**$H_3$: Seasonality Effect**

The third hypothesis was concerned with how good people were at dealing with seasonality contained in time series and if this is anyhow related to information modality. We found that judgmental forecasting of seasonal series appeared to be less accurate than that of non-seasonal time series (29.57 vs. 19.82) (F=81.396, p<.005) and this was also evident with all subjects included (20.35 vs. 30.22) (z=-6.566, p<.005). Interestingly enough, however, people seemed to forecast differently in dealing with the seasonality of time series depending on the way it was presented (F=14.365, p<.005) (see Figure 4). Display format did not affect forecasting accuracy of nonseasonal series whereas it did for seasonal series (20.46 vs. 20.28). That is, people appeared to perform with seasonal series significantly better when presented in a tabular format than in a graph format (27.03 vs. 32.06). It is quite contrary to proposition that graph would be good at revealing patterns contained in time series. ANOVA presented in Table 3 also showed an interaction of seasonality with emotion and information modality as well (F=4.998, p<.05). Table 6 shows that people in good emotion seemed to perform quite well even with seasonal series presented in table. It was not evident in other conditions. Taken together, the hypothesis was accepted.

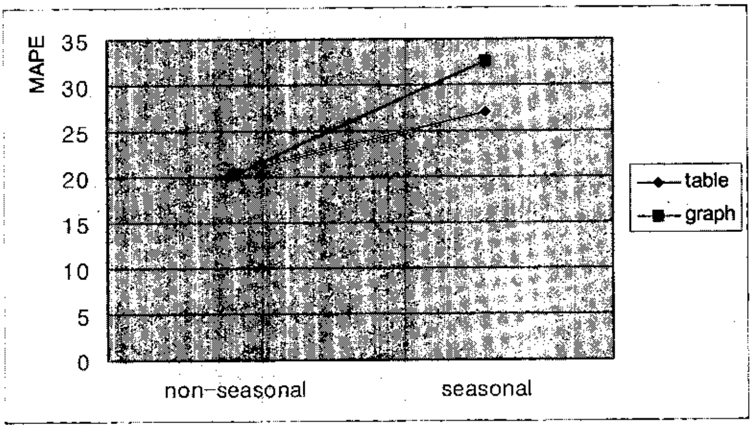


Figure 4 : Interaction between seasonality and display format

H4: Learning Effect

Learning effect was found in this study. People appeared to perform better gradually over time (F=2.915, p<.05). This effect was more evident for seasonal series and this suggests that people were able to take advantage of seasonal patterns contained in the time series over time. On the other hand, people did not seem to learn non-seasonal series (F=4.008, p<.01). It should be, however, noted that overall judgmental forecasts for non-seasonal series was significantly more accurate than for seasonal series. This suggests that people appeared to take the best guest strategy for the patterns contained in time series which possibly led to a worse performance

Table 7 : MAPE Means for Seasonality x Trial Conditions

| | | non-seasonal | seasonal | AVERAGE |
|---|---|---|---|---|
| num rolls | 1st | 17.24 | 33.10 | 25.17 |
| num rolls | 2nd | 22.30 | 31.88 | 27.09 |
| | 3rd | 19.24 | 26.78 | 23.01 |
| | 4th | 20.50 | 26.53 | 23.52 |
| AVERAGE | | 19.82 | 29.57 | 24.70 |

## 4. Experiment 2

We found in the earlier experiment that emotion along with information modality may affect they way people make forecasts. The second experiment focused on how forecasting accuracy is related to brain activities. Employing the time series identical to those of the experiment 1, this study was designed simply to record physiological activities over the task of judgmental forecasting. It is generally accepted that alpha and beta activities are associated with cognitive tasks. Yet the empirical evidence regarding the exact nature of the relationship appears to be confounding. A view that receives a wide acceptance is a phenomenon of alpha desynchronization and beta synchronization (Fernandez et al., 1995). That is, alpha activity appeared to be more evident in a general relaxed mental state and decrease with mental efforts (Andreassi, 1989). Then beta rhythms appear to be augmented as alpha activity is desynchronized (i.e., alpha blocking). Since alpha power appeared to be inversely related to mental effort (e.g., Butler & Glass, 1976; Donchin, Kutas, & McCarthy, 1977; Glass, 1964) and indicative of transient paucity of mental activity (Adrian & Mathews, 1934; Lindsley, 1952), it may be deduced that good performance is possibly associated with higher levels of alpha blocking. Along with alpha blocking, changes in the beta band can be found with cognitive efforts (Gevins et al., 1979; Tucker et al., 1985; John et al., 1989; Ray & Cole, 1985).

While this notion of inverse relationship between alpha and beta rhythms, there has been some empirical evidence that alpha activity is not necessarily blocked during mental tasks. Darrow (1947) argued that alpha is associated with the automation or habituation of learned behaviors. Accordingly, alpha activity may increase during the performance of some mental tasks. Indeed, there exists a line of research that upholds the possible contribution of alpha activity to good performance in mental tasks (Krause, 1992 from Jausovec, 1996: 159; Juolasmaa et al., 1986; Legewie et al., 1969; Jausovec, 1996). As discussed earlier, this is contrasting to the view that the reduction of alpha power is associated with good performance (Earle, 1988). This may be due to the capability of good performers not to use many brain areas not required for the problem at hand (Jausovec, 1996). This study shall investigate the changes in alpha and beta activity during mental tasks, in particular in frontal areas that is known to be associated with mental tasks (Petsche et al., 1986). A nulll hypothesis is that there is no relationship between forecasting accuracy and alpha and beta in EEG.

EEG (ElectroEncephaloGram) was measured based on the 10-20 systems (Jasper, 1958) at two positions: (1) occipital and (2) frontal sites of the brain (Oz, Fz). This was due to the fact that the experimental task required the subjects to process visual time series information (i.e., occipital) in need of much cognitive efforts (i.e., frontal, Petsche, 1992; Inouye et al., 1933). Twelve under- and postgraduate students participated in the experiment as part of their course. Subjects were asked to sign up the experiment individually according to the time schedule. On entering the experimental room, subjects were seated and briefed about the types of incentives and the tasks that they were required to perform. Then, in order to measure EEG and GSR, physiological gadgets were attached on the subjects (brain, finger, ankle, etc.). They were ushered into the experimental room. They were asked to sit and relax for 1 minute with their eyes closed. Then, subjects were asked to open their eyes and look at the time series for 1 minute. With physiological recording paused, subjects were asked to project 8-period ahead forecasts for the given time series. The above task of judgmental forecasting was repeated with eight different times series. This experiment was performed in one sitting. They were provided with $5 worth reward.

Initial 15 and 30 second segments were taken from EEG and GSR over the task of time series forecasting. FFT analyses were performed to obtain alpha and beta rhythms with which beta/ alpha ratios were also computed for statistical analyses. Then, correlational analysis was performed with forecasting accuracy (MAPE). The results indicated that frontal beta was the one that accounted for accuracy. The accuracy tended to be high when beta was relatively higher than alpha. That is, there was a positive relationship between beta and the accuracy ($r=-.080$, $p<.05$). Therefore, frontal beta was related to accuracy. We also found that GSR was significantly correlated with forecasting accuracy ($r=-.115$, $p<.005$). However, there was different beta variation with the accuracy between frontal and occipital area. Frontal beta increased but occipital beta decreased with the accuracy($r=.081$, $p<.05$). The negative correlation between occipital beta variation and the accuracy was shown to become clearer with task duration for 30 second($r=.221$, $p<.005$). This could be explained by affect of cognitive strain on occipital beta variation.

## 5. Discussion

Although emotion plays a critical role in decision making, very scarce research has been made to directly address the effect of emotion on decision accuracy. This study was conducted to examine the effect of emotion along with information format on time series judgmental forecasting and its accuracy. Personality and psychology literature suggests that one's emotional state influences decision making. That is, people when they are forced to feel sad tended to be more analytic than those in happy mood. It is, however, not clear yet that such analytic approach to problem leads to accuracy improvement. We found that emotion did not affect directly forecasting accuracy. Interestingly enough, however, it seemed to intervene judgmental forecasting depending upon the way time series was presented. That is, people in good emotion seemed to discern seasonality contained in time series when presented in tables better than those in bad emotion.

We also looked at the issue of information display and its relationship with the effect of emotion on forecasting accuracy. The results of this study suggest that graph could possibly lead to more error-prone forecasting. DeSanctis (1984) claimed that its benefit is in doubt after having reviewed earlier empirical research. Indeed, some studies argued that people made more accurate forecasts with graphs than did they with tables (DeSantics & Jarvenpaa, 1989). On the other hand, some claimed inferiority of graph to table (Powers et al., 1984), in particular for such tasks of less complexity (Remus, 1987) and little pattern (Umanath et al., 1990). Benbasat and Dexter (1985) reported little contribution of graphs to decision quality over tables. Benbasat et al. (1986) claimed that graphs may be beneficial in reducing time of processing information as found in this study. This may be due to adequate amount of learning required for understanding the information presented in graph format (Ives, 1982). One may question that graph could have been designed in better formats. Aldrich and Parkin (1987) designed three different line graphs depending upon the existence of grid assistance and failed to show that this design factor could make difference in accurately reading X-Y coordinates. Such skeptic results with the efficacy of graph may be due to that it could have let people overlook the complexity of the task and try to minimize their cognitive efforts. Indeed, graph was found to let people spend less time, which might have led to performance deterioration.

This paper employed a physiological approach to tap into its cognitive processes and explore what brain waves contribute to good performance. Physiological data obtained in this study suggest that this may be due to some intervening effect of EEG. Forecasting accuracy appeared to be positively correlated with frontal beta. Alpha (8-12 Hz) and beta (13-50 Hz) have been of interest to examine the relationship between EEG and the performance of cognitive tasks. It is now generally accepted that alpha and beta activities are associated with cognitive tasks (Ray & Cole, 1985; Nunex, 1995). Yet the empirical evidence regarding the exact nature of the relationship appears to be confounding (Fernandez et al., 1995; Cabrera, 1988). Despite a number of studies regarding alpha and beta changes in relation to mental tasks, very limited studies directly investigated its effect on decision making and performance. Findings from attention studies offered little support for a consistent relationship between performance decrement and any EEG frequency (Morrell, 1966; Daniel, 1967; Boddy, 1971; Gale et al., 1972; O'Hanlon and Beatty, 1977; Townsend and Johson, 1979; Belyavin & Wright, 1987). There have been, however, a number of empirical studies to suggest that the power of frontal beta appear to be associated with decision performance.

Main findings for the effect of emotion on EEG are asymmetrical results that more beta being present in the right temporal area during positively as opposed to negatively valenced emotional tasks (Ray and Cole, 1985; Sobotka et al., 1992). Recent electrophysiological evidence suggests that the locus of this asymmetry lies in the frontal lobes (Davidson, 1982). In addition to asymmetrical allegation of EEG to emotion, emotion may affect EEG in various ways such as (1) suppressed alpha (e.g., Lindsley, 1951; Guiterrez and Cabrera, 1988; Wheeler, et al., 1993), (2) increased frontal beta (Cohn, 1946; Shpiberg, 1947; Faure, 1950) and (3) increased alpha and decreased beta (Thiesen, 1941). To be consistent with the findings of the earlier studies, the power of frontal beta was found to be an indicator of negative emotion. Interestingly enough, frontal beta appeared to contribute to an improvement of forecasting accuracy.

The results of this study should be generalized with caution. First, emotion is by no means easy to manipulate. We measured it by asking the participants to report what they felt. In a lab setting, however, it could be fabricated or influenced by extra experimental conditions. There was in this study a tendency that manipulation to let subjects feel better seemed to work for those who initially tended to have bad emotion and vice versa. It should also be noted that people tended to report mid emotion rather than extreme one (e.g., 1 or 5 on a Likert scale). The insignificant difference in performance between the good and the bad motion group may not hold true with more extreme emotion. It would be also interesting to replicate this study using other stimuli to manipulate emotion. Thirdly, inferiority of graph to table may be due to the lack of training given to the subjects. Given that learning was not found in using graph in this study, however, further research is urged on this issue of the usefulness of graph in time series forecasting. Lastly, it should be noted that this study observed ipsilateral asymmetry in contrast to translateral asymmetry of the earlier studies (Davidson, 1990). As discussed earlier, however, the results of this study corroborated with those of earlier studies. In addition, individual differences in subjects EEG (Galbraith and Wong, 1983) were not considered in this study assuming that the normal EEG can be stable intraindividually (Gasser et al., 1985). This study may be valuable to forecasting practitioners and researchers in understanding the cognitive process of time series judgmental forecasting by exploring its psychophysiological measures. For example, in a time series context, the results obtained in this study may provide a clue to the dampening behavior for the down-trended time series. This study also contributes to the academic field of forecasting and decision making in that the effect of emotion was studied with physiological measures of EEG and GSR. EEG may be used as a powerful instrument for gaining insights into the cognitive process of judgmental forecasting as well as decision related studies.

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# A Study on Emotion and EEG to Improve the Accuracy of Judgmental Time Series Forecasting in a Web-based Computer Task

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Keywords: emotion, forecasting, judgment

***Abstract*** Although emotion plays a critical role in decision making, little has been known as to its effect on judgmental time series forecasting. The research was conducted as a 2 (emotion) x 2 (display) x 2 (seasonality) x 4 (trials) factorial design with repeated measures. Emotion was induced by positive feedback and incentives provided depending on task performance. Time series (seasonal & nonseasonal) was presented in different format (either graphical or tabular). Subjects were 86 under- and postgraduate students. The results indicated that emotion did not appear to affect directly forecasting accuracy. Emotional states, however, seemed to influence the way people processed information, which could have possibly led to difference in performance. In particular, people in good emotion seemed to process seasonal information of time series presented in table better than did those in bad emotion. An additional experiment was carried out to investigate into what brain activities contributed to good performance in judgmental forecasting. We found that beta activities at frontal sites may have contributed somewhat to accuracy improvement.