The effect of positive mood on intention to use computerized decision aids

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Abstract

While psychology research has indicated that positive mood enhances cognition and behavior, MIS researchers have largely ignored such potential effects on user acceptance of new IT. Using two cognitive theories on mood and memory, positive mood theory and the affect infusion model (AIM), we developed hypotheses about the contribution of these mood conditions on user acceptance of new IT with two levels of uncertainty. These hypotheses were investigated via an experiment using a computerized decision making aid. We found that positive mood increased acceptance, under both levels of uncertainty. These results held for both induced and naturally occurring positive mood. The results were consistent with positive mood theory but not with the AIM.

Keywords: Mood; Affect; Uncertainty; Computerized decision aids; Behavioral intention; Technology acceptance; Human computer interaction

1. Introduction

A growing body of research suggests that positive mood enhances cognition and behavior. Even small positive events, such as receiving a small gift, bring about significant changes in thought processes and behavior. Two prominent theories have been developed to explain the effect of positive mood on cognitive processes and resulting behaviors: positive mood theory [21] and the affect infusion model (AIM) [9]. Based on these, investigators have explored the effects of positive mood in the areas of social behavior and cognition (see [20]). Their work suggests that the mood state of users may affect users’ initial acceptance of an IT. However, they have received little attention in the MIS literature.

MIS research has recognized affective constructs such as attitude (the degree to which a person likes or dislikes the object), computer playfulness, and perceived enjoyment [29] but not Mood, which captures “how people feel at work or when they are on the job, not necessarily how they feel about work” [12]. MIS research using affective constructs has primarily focused on affective reactions toward the use of technology and not the affective state of users when they are introduced to IT. We investigated the feeling state of users at the time they first used a new IT, rather than their feelings toward using it. Thus our study examined positive mood – an affective construct that has been shown to have a significant influence on behavior.

We hypothesized that positive mood can enhance the acceptance of an IT even when uncertainty is high and developed an experiment to test the effects of positive mood on acceptance of a computerized decision aid under two distinct levels of uncertainty. This laboratory-based experiment provided the necessary control to manipulate users’ mood and the uncertainty of the information available to users.

2. Positive mood theories

It is important first to explain how the term mood is used in our paper. First, although mood can be considered to be a state or a trait, in our study it is a state variable because one’s feeling state has a significant influence on cognition and
behavior. Second, we examined the mood of the subjects and not their emotions. Moods and emotions differ in their degree of “pervasiveness”, “intensity”, and “specificity”. Emotions generally denote short-lived strong reactions that often have both a specific cause (e.g., a provocative act) and a target (e.g., anger). Moods are less intense, but enduring and diffused affective states not directed toward any particular object or behavior. Third, mood states can be grouped into general categories (positive, neutral, and negative) [2] and we chose to focus on the effects of positive mood using two theories positive mood theory and the affect infusion model. Although these two theories take different ways to explain the effect of positive mood on cognitive processes, both suggest that positive mood acts as an effective retrieval cue for positive material in memory and argue that positive mood influences the evaluation of stimuli.

According to positive mood theory, positive material is diverse, rich and flexible, and a positive mood cues positive material in memory. Thus, when in this state one has access to a rich and elaborately connected network of cognitive positive material. Indeed, research has shown that positive mood can significantly enhance cognitive ability and behavior. Positive mood promotes an explorative behavior or greater willingness to try new products; people tend to integrate new information more efficiently, be less confused or overwhelmed, and exhibit a better understanding of the issues. These effects are supported by a study proposing the “dopaminergic” theory, which suggests that the release of dopamine into the brain may underlie the relationship between positive affect and enhanced cognitive processes [19].

The AIM also argues that mood and memory are connected; mood states are directly linked to cognition within a single associative network of mental representations. The mood states cue thoughts as they selectively activate memory nodes to which they are connected. Thus, the AIM suggests that positive mood cues positive material in memory.

Both theories argue that moods can be induced by ordinary events in everyday life. In particular, positive mood can be induced by simple things, such as viewing short clips of non-aggressive comedy films, thinking positive thoughts, success on an unrelated task, or working in a room with a pleasant atmosphere [18].

A difference between the two theories exists in their explanation of the effect of positive mood on processing style. AIM predicts that positive mood promotes a processing style that relies on internal schemas and data to respond to a situation. The positive mood theory argues that positive mood facilitates a processing style responsive to both internal and external information.

Another disagreement between them is the role of uncertainty on mood effects. AIM suggests that affect congruent effects take place when tasks require creative processing and active generation of new information, e.g., when “people face uncertain and unpredictable social encounters” for which they need to interpret indeterminate cues [8]. AIM predicts that positive mood effects are more likely to take place in the presence of uncertainty and that the effects of positive mood on cognition and behavior are intensified when more extensive processing is required, e.g., when dealing with a demanding, complex, or uncertain task. For example, an individual performing a more uncertain task produces a more positive evaluation of stimuli. Although the positive mood theory also suggests that the nature of the task can mediate the effects of positive mood, it does not suggest that a more demanding, complex or uncertain task results in intensified mood congruent behavior.

Our study investigated the effects of positive mood on acceptance, which is supported by both theories. It also investigated which one of the predictions about mood effects under high uncertainty was verified.

3. Research model and hypotheses

We developed a basic model of the effects of positive mood on intention to use a new decision aid, and tested this model via a laboratory-based experiment that involved two levels of uncertainty. Our research model and the hypotheses are shown in Fig. 1.

3.1. Effect of positive mood

The main objective of acceptance studies is to examine why individuals adopt a new IT and what could be done to improve the acceptance of new IT. Acceptance studies have examined various antecedents to users’ intention to use IT, since intention is closely linked to actual behavior. These antecedents, included usefulness, ease of use, playfulness, security [13], risk, cost, fashion involvement [26], and satisfaction with the task support [11], are often chosen by tailoring psychological theories to examine individuals’ reactions and behavior to a new IT. These antecedents have been investigated using regression or ANOVA, and sometimes using SEM with LISREL, AMOS, or PLS.

Theories have also suggested that behavior is influenced by the first, immediate thoughts [28], which in turn are affected by the user’s mood. While mood represents only

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**Fig. 1. Research model.**

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one of many constructs that capture some aspects of human feelings, the literature has suggested that positive mood is likely to help in refining our understanding of acceptance behavior as our other human feelings. The literature provides compelling theories and empirical evidence of the enhancing effects of positive mood on cognition and behavior, which suggests that positive mood primes positive thoughts in the cognitive system and promotes explorative behavior and influences the evaluation of stimuli. For a detailed review see [17].

In our searches, we found only two studies that examined the effect of mood on IT acceptance indicators [31,33]. The Woodroof and Burg study examines the effect of negative affect (as a trait variable) on user satisfaction with an IT. The Venkatesh and Speier study examined the effect of mood on motivation during training and thus measured positive mood as a state variable and examined its effect on intention to use an IT. Our study focused on acceptance and thus induced positive mood before the experimental use of the system for a task, providing a more direct test of positive mood effects on acceptance. Our first hypothesis replicated the results of Venkatesh and Speier and extended it by providing a more direct test of mood effects on acceptance.

**H1.** Individuals in the positive mood treatment will have greater intention to use the computerized decision aid as compared to individuals in the control group.

The literature has suggested that positive moods are common and that the effects of positive mood on cognition are robust and independent of the mood inducement method [10]. Thus, it is reasonable to expect that positive mood, whether naturally occurring or induced by the experimenter should have a similar effect on intention to use. Thus, we tested the effects of naturally occurring mood by testing the effects of mood within the control group:

**H2.** For individuals in the control group, the higher the mood scores, the greater their intention to use the computerized decision aid.

### 3.2. Effect of uncertainty

We used a judgment task to test our hypotheses; it was a cognitive process in which a person made a decision about an unobserved event (or criterion) on the basis of a set of data. Many decision making and decision support studies have used judgment tasks in studying human decision behavior. For example, our task was used in several prior DSS studies including one examining acceptance decisions [6]. When making a judgment, one has to estimate the relationship between the available information and the criterion and combine the information into a single judgment. Judgment tasks are inherently uncertain because they require decision makers to interpret indeterminate information.

While both positive mood theory and the AIM suggest that positive mood affects cognition and behavior, the AIM also suggests that the effects of mood are intensified under more uncertain tasks. To examine these predictions, we created two levels of uncertainty in our judgment task. Consistent with AIM, seemed reasonable to argue that intention to use was more favorable for individuals in the positive mood treatment with the more uncertain task.

**H3a.** For individuals in the positive mood treatment, those with the more uncertain task will have greater intention to use the computerized decision aid as compared to those with the less uncertain task.

Although positive mood theory agrees with AIM that the nature of the task can influence the effects of positive mood on behavior, it does not suggest that higher levels of uncertainty will result in stronger mood effects. Nor does it suggest that the mood effects will be less strong for more uncertain tasks. Thus, we also tested for a no-differences version of hypothesis 3.

**H3b.** For individuals in the positive mood treatment, there will be no significant difference in intention to use the computerized decision aid between those with the more uncertain task and those with the less uncertain task.

Hypotheses **H3a** and **H3b** examined the effects of uncertainty on the effect that induced positive mood can have on intention to use a computerized decision aid. Since positive mood effects on cognition are robust regardless of the mood inducement method [22], it is reasonable to expect that these uncertainty effects also extend to naturally occurring positive moods. Thus, the following hypotheses were enunciated for the control group.

**H4a.** For individuals in the control group, the mood congruent effect on intention to use (i.e., the higher the mood scores, the greater the intention to use the computerized decision aid) will be significantly stronger for those with the more uncertain task as compared to those with the less uncertain task.

**H4b.** For individuals in the control group, the mood congruent effect on intention to use (i.e., the higher the mood scores, the greater the intention to use the computerized decision aid) will not be significantly different for those with the more uncertain task as compared to those with the less uncertain task.

### 4. Research method

#### 4.1. Design of the laboratory experiment

The hypotheses were tested using a laboratory experiment because it would then be possible to provide control over the task, uncertainty, and mood. The judgment task required multiple judgments over time; these required user
interpretation because of the probabilistic and uncertain nature of the information. The task was embedded in a computerized decision aid that was new to the subjects, thus providing a context for measuring intention to use.

The experiment used a 2 X 2 design with two levels for mood (positive and control) and two levels for uncertainty (low and high). Each subject was randomly assigned to one of the four conditions. The subjects were 134 (60 male and 74 female) undergraduate business students from four sections of a third year business statistics course at a major US land grant university. The results of the power analysis [3] showed that with this sample \( n = 134 \), medium effects could be detected with a power of 0.95 and small effects could be detected with a power of 0.80.

4.1.1. Mood treatment

The subjects in the positive mood treatment received a surprise gift of chocolate and candy wrapped in colorful paper a few minutes prior to performing the task. Mood manipulation was disguised by presenting the gift as a small token of appreciation for taking the test. Participants in the control group did not receive a gift.

4.1.2. Mood measurement

A self-reporting survey was used to measure the subjects’ mood. Subjects were asked to rate on a seven-point scale (with 1 denoting “strongly disagree”, 4 denoting “neutral”, and 7 “strongly agree”) how each of the words “glad”, “happy”, “pleased” described their current mood. These words were used in a mood manipulation survey created by Elsbach and Barr [7]. To measure mood, they employed words from the Dictionary of Affect [32] describing feeling states that were high on the dimension of pleasantness.

The items on the survey were shown to be strongly related (\( \alpha = 0.89 \)). We verified the internal reliability of the items. Our test of reliability showed a strong relationship among the items on the survey (\( \alpha = 0.89 \)). Consistent with prior research, for each subject a composite mood score (CMood) was calculated: the ratings for the happy, glad, and pleased were averaged to calculate the mood for each subject.

4.1.3. Task description

The task was a manufacturing problem based on Holt et al.’s [16] model of the production-scheduling problem. This has been used in many previous experiments. The problem was to decide how many units to produce given uncertain future demand and knowledge of the size of the work force, productivity, and inventory.

This production-scheduling problem was selected because it is a managerially relevant problem appropriate for the subjects used in the experiment. Judgment tasks are often used to measure how people learn to improve their judgment. Thus, this type of task is appropriate for subjects who have no prior experience with such a task [5]. Furthermore, this task has been calibrated with real data in making production-scheduling decision at Pittsburgh Plate Glass.

The production-scheduling decision is modeled through the following equation:

**Production decision**

\[
\begin{align*}
&= b_{10} + b_{11} \text{ (work force last month)} \\
&- b_{12} \text{ (inventory on hand)} \\
&+ b_{13} \text{ (the current month’s demand)} \\
&+ b_{14} \text{ (the demand for next month)} \\
&+ b_{15} \text{ (the demand for two months ahead)}
\end{align*}
\]

where the coefficients values are \( b_{10} = 148.5, b_{11} = 1.005, b_{12} = 0.464, b_{13} = 0.464, b_{14} = 0.239, \text{ and } b_{15} = 0.113 \).

The decision rule in Eq. (1) describes a perfect world with no uncertainties. To mimic the real world with its uncertainties in an experimental setting, an error term is generally added:

**Production decision**

\[
\begin{align*}
&= b_{10} + b_{11} \text{ (work force last month)} \\
&- b_{12} \text{ (inventory on hand)} \\
&+ b_{13} \text{ (the current month’s demand)} \\
&+ b_{14} \text{ (the demand for next month)} \\
&+ b_{15} \text{ (the demand for two months ahead)} + e
\end{align*}
\]

The computerized decision aid provided subjects with scheduling information (demand, inventory, etc.). While the decision aid was tailored to this particular task, it provided information and computations typical of a decision aid designed to support operational-level decisions. The subjects entered their judgments (production-scheduling decision) by adjusting a slider or using a scrollbar to set their desired value. A small window on the bottom right corner of the screen displayed a message to motivate subjects to do their best. A judgment was submitted by clicking the button “I am satisfied with my current decision.” Once this button was pushed the subject’s judgment (the production value), the actual judgment (generated by the model in Eq. (2)), and the percentage error of the subject’s judgment (outcome feedback) was displayed in a dedicated section of the screen. A short history of the subject’s five most recent judgments along with the actual judgments and the percentage error were also displayed. At the same time, the window that displayed the motivational message was replaced by another window displaying the value of the actual judgment (the production value generated by the model in Eq. (2)) in a large font. A button labeled as “OK to Continue” was also displayed. This button was used to start a new trial (i.e., a new set of randomly determined and statistically independent cue values).
The production-scheduling task involved 35 trials. The lower limit for the number of trials in a judgment task with low to zero cue correlation was determined by the number of cues in the task. The literature suggested a “5 to 1” ratio (five trials for each cue) for the minimum number of trials. The upper limit for the number of trials was often determined by the available time [27]. Many studies (including ours) selected the number of trials by starting with the minimum and adding some extra ones [25]. We provided 10 extra trials in addition to the required minimum (5 trials for each of the 5 cues + 10 extra trials = 35 trials).

4.1.4. Uncertainty treatment and measurement

Uncertainty in a judgment task is calculated through the correlation between the optimal criterion (production decision of Eq. (1)) and the actual criterion (production decision of Eq. (2)). Thus, the level of uncertainty is controlled through the error term added to the task by the use of Eq. (2).

In our study we used two different error terms to generate the uncertainty levels $U_1$ and $U_2$ ($U_1 < U_2$). To create these, a set of error terms and their corresponding predictabilities (Re) were generated in a simulation. The error term $e = 100$ with its corresponding predictability level $Re = 0.75$ was selected to generate the uncertainty level $U_1$. Because this error term had been used in many prior studies [24], this served as a point of reference. The second uncertainty level was selected to make the task information less predictable. We used $e = 188$ with its corresponding predictability level $Re = 0.55$ to represent $U_2$. Naylor and Schenk [23] showed that decision makers’ achievement significantly decreased as their task predictability decreased from 0.9 to 0.7 to 0.5. Since these levels differ by 0.2 points, the predictability of the less certain task in our study was selected to produce $Re = 0.55$.

A pretest was conducted to establish that the two uncertainty levels were significantly different (whether there was significantly lower judgment quality for the more uncertain task). To verify this, we compared subjects’ task achievement, i.e., their judgment quality. Judgment tasks such as ours required the task performer to make a prediction about the likelihood of a future event. Achievement reflects how closely subjects’ judgments and the criterion values match [15].

The pretest used 43 subjects randomly assigned to either uncertainty level. Subjects’ achievement was measured through the correlation between subjects’ judgments (decision values entered into the computerized decision aid) and the actual criterion (production decisions calculated by the linear model of Eq. (2)) [14]. The results of this pretest showed that the subjects’ achievement was significantly lower under the more uncertain task ($Mean_{U_1} = 0.58$, $Mean_{U_2} = 0.34$, $t = 2.97$, $p = 0.002$). Thus, the results of the pretest showed that results for the two uncertainty levels were significantly different. All the pretest subjects completed their task (35 trials) within the allocated time of less than 1 h.

4.1.5. Behavioral intention measurement

Behavioral intention to use the computerized decision aid was measured using the validated scale from Venkatesh and Morris [30]. This has been used in many prior studies [34]. The test for internal reliability of these items confirmed previous findings and showed a strong relationship among the items of the survey ($alpha = 0.98$).

To ensure validity of BIU in this context, subjects were told that the decision aid was designed to be used in business courses (including the course they were attending) as a way of practicing decision making.

4.2. Procedure

4.2.1. Assigning subjects to treatments

Each subject was randomly assigned to one of the four conditions. The 134 subjects were from four sections of the same course. The experiment was conducted over four consecutive days of the same week. The subjects were randomly assigned to these four days so that each section of the course was equally represented in the positive and control mood groups. Subjects attended only the session to which he or she was assigned: no class sessions were held during that week.

The mood of the subjects who were assigned to the Tuesday and Wednesday groups was not manipulated; these students served as the control group. The mood of the subjects who were assigned to Thursday or Friday was manipulated by giving them the surprise gift. Thus, these subjects served as the positive mood group. The mood manipulation was conducted in the last two days of the experiment to control for the possibility of mood contamination (subjects on Thursday or Friday might have learnt about the gift given previously). All subjects were instructed not to talk about the experiment until a week after it was completed.

We examined our data to ensure that there were no systematic differences within the positive mood intervention sessions and the control group sessions. The results of the $t$-test showed no significant difference between the two sessions in the positive mood treatment or between the two sessions in the control group. Thus, we pooled the data gathered from the two sessions for the positive mood treatment and also pooled the data within the control group sessions.

4.2.2. Running the experiment

For the experiment, participants gathered in their normal classroom. On arrival, they received a card with a randomly assigned seat number to eliminate situations that might affect their mood (e.g., sitting near a friend or in a favorite spot).
The same instructions were read to all groups by the same person. Subjects were informed that this experiment investigated managerial decision making and that the software package that they would use was designed to assist business students in learning and practicing managerial judgments and that it was being considered for use in the current and other courses.

The subjects were given a short tutorial on the task; then those in the positive mood treatment received the gift while subjects in the control group did not. Subjects were then asked to go to their designated pre-assigned computers in the laboratory. The task in the computerized decision aid was set at either the high or low uncertainty level.

The subjects activated the software package that included the mood survey, two practice trials, and the actual task with 35 trials. Each part had to be completed before the next appeared. After finishing, the subjects were debriefed and asked to leave the room.

4.3. Analysis

We used SPSS to perform our analyses. For hypotheses about differences between the treatment groups, we used \( t \)-tests to compare behavioral intention to use (BIU) for the positive and control mood treatment in H1 and the two uncertainty treatments in H3. We used regression to analyze the effect of mood scores, a continuous variable, on intention to use the computerized decision aid (H2). To test whether uncertainty moderated the relationship between mood and intention to use, as predicted by H4, we followed the method of Baron and Kenny [1]. Since mood (CMood) and BIU are represented by continuous variables and uncertainty by a binary variable, this method involved running two separate regressions (i.e., CMood against BIU using one regression for each uncertainty level, and comparing the slopes to test whether the unstandardized regression coefficients were significantly different [4]).

5. Results

First, an uncertainty manipulation check was conducted to verify that the uncertainty levels were significantly different. Then, a mood manipulation check was carried out to test whether positive mood was successfully induced. Next, descriptive statistics were run for each treatment. Finally the hypotheses were tested.

5.1. Uncertainty manipulation check

The pretest check of significant differences between the two uncertainty levels was repeated for the experimental subjects. Like the pretest, we compared subjects’ achievement under the uncertainty levels. To exclude possible mood effects, this comparison was done for the subjects in the control group only (\( n = 63 \)).

<table>
<thead>
<tr>
<th>Uncertainty level</th>
<th>Achievement</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( U_1 ) (low)</td>
<td>0.52</td>
<td>0.20</td>
</tr>
<tr>
<td>( U_2 ) (high)</td>
<td>0.35</td>
<td>0.20</td>
</tr>
</tbody>
</table>

\( d.f. = 61, t_{-}\text{-Stat} = 3.46, p < 0.001 \).

The results of the one tail \( t \)-test for achievement, measured as the correlation between actual criterion (decision values calculated using the model in Eq. (2)) and subjects’ decisions (decision values entered into the computerized decision aid by the subjects), showed that the achievement of the subjects with the lower uncertainty level was significantly higher than the achievement of the subjects with the more uncertain task (Mean\( U_1 \) = 0.53, Mean\( U_2 \) = 0.33, \( t = 3.73, p < 0.01 \)), see Table 1. That is, subjects’ achievement was significantly worse under the more uncertain task. Thus, these results confirmed that uncertainty was successfully manipulated.

5.2. Mood manipulation check

The results of this check showed that positive mood was successfully induced. The one tailed \( t \)-test showed that the mean of the composite mood scores, CMood, of the subjects in the positive mood treatment was significantly higher than the mean of the CMood of the subjects in the control group (MeanPositive Mood Treatment = 5.04, MeanControl group = 4.65, \( t = 1.99, p = 0.02 \)), see Table 2.

5.3. Descriptive statistics

The basic descriptive statistics for the CMood and dependent variable, BIU, broken down by treatment condition, is given in Table 3.

5.4. Positive mood hypotheses

Hypothesis 1 asserted that individuals in the positive mood treatment would have greater intention to use (their decision aid than those in the control group. The results of the one tail \( t \)-test showed that the mean of the variable BIU was significantly higher in the treatment group, see Table 4, thus supporting H1.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>CMood</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive mood group</td>
<td>5.04</td>
</tr>
<tr>
<td>Control group</td>
<td>4.65</td>
</tr>
</tbody>
</table>

\( d.f. = 132, t_{-}\text{-Stat} = 1.98, p = 0.02 \).
Hypothesis 2 stated that the effects of positive mood would hold regardless of whether the positive mood was induced or naturally occurring. Since this hypothesis pertains to naturally occurring positive moods, it was tested for the subjects in the control group \((n = 63)\). To test this assertion, a regression model in the form of Eq. (3) was used.

\[
BIU = b_0 + b_1 CMood
\]

where \(BIU\) represents the self reported intention to use scores and \(CMood\) captures the composite mood scores of the subjects in the control group.

The results showed that 20\% \((R^2 = 0.20)\) of the variation in \(BIU\) was explained by the regression equation. Moreover, there was a significant effect for the variable \(CMood\) \((b_1 = 0.44, t = 3.86, p < 0.001 \text{ one tail})\), as shown in Table 5. These results indicate that the more positive the mood, the higher the subjects’ \(BIU\) scores. \(H_1\) predicted that individuals in the positive mood treatment would have higher \(BIU\) scores than those in the control group. The results of \(H_1\) and \(H_2\) together indicated that there are no discrepancies between the effects of induced and naturally occurring positive mood.

### 5.5. Uncertainty hypotheses

Hypothesis 3a asserted that the individuals in the positive mood treatment who completed the more uncertain task will have greater intention to use the aid as compared to their counterparts who completed the less uncertain task. Hypothesis 3b asserted that there would be no significant difference between the \(BIU\) scores of individuals in the positive mood treatment who complete the more uncertain task and their counterparts who completed the less uncertain task.

The results of one tail \(t\)-test show that the \(BIU\) scores of the subjects in the positive mood treatment with the high uncertainty task were not significantly different from those with the low uncertainty task (see Table 6). Thus, these results support Hypothesis 3b but not 3a.

Hypothesis 4 predicted that the same pattern of behavior as that of hypothesis 3 holds for naturally occurring positive mood. Hypothesis 4a predicted that the effect of positive mood on intention to use the aid was intensified under the more uncertain task. Hypothesis 4b predicted that there would be no significant difference due to level of uncertainty. Once again, we tested these using the subjects in the control group \((n = 63)\).

Hypothesis 4 examined the moderating effect of uncertainty on the relationship between mood and \(BIU\). We needed to examine the effect of \(CMood\) on \(BIU\), using a linear model similar to that in Eq. (3), for the two uncertainty levels. The test of difference between the unstandardized

### Table 3
Descriptive statistics by treatment

<table>
<thead>
<tr>
<th></th>
<th>Control group</th>
<th>Positive mood treatment</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CMood</td>
<td>BIU</td>
<td>CMood</td>
</tr>
<tr>
<td>Uncertainty (U_1)</td>
<td>4.76 (1.15)</td>
<td>4.73 (1.11)</td>
<td>4.95 (0.94)</td>
</tr>
<tr>
<td>(N = 31)</td>
<td></td>
<td></td>
<td>(N = 35)</td>
</tr>
<tr>
<td>Uncertainty (U_2)</td>
<td>4.55 (1.07)</td>
<td>4.30 (1.22)</td>
<td>5.11 (1.21)</td>
</tr>
<tr>
<td>(N = 32)</td>
<td></td>
<td></td>
<td>(N = 36)</td>
</tr>
<tr>
<td>Total</td>
<td>4.65 (1.11)</td>
<td>4.51 (1.17)</td>
<td>5.04 (1.08)</td>
</tr>
<tr>
<td>(N = 63)</td>
<td></td>
<td></td>
<td>(N = 71)</td>
</tr>
</tbody>
</table>

Statistics in each cell are mean (S.D.); number of subjects.

### Table 4
Results of hypothesis 1

<table>
<thead>
<tr>
<th>Treatment</th>
<th>BIU</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive mood group</td>
<td>4.86</td>
<td>1.21</td>
</tr>
<tr>
<td>Control group</td>
<td>4.51</td>
<td>1.17</td>
</tr>
</tbody>
</table>

d.f. = 132, \(t\)-Stat = 1.72, \(p = 0.04\).

### Table 5
Results of hypothesis 2

<table>
<thead>
<tr>
<th>Variable</th>
<th>(b)-Value</th>
<th>(t)-Value</th>
<th>(p)-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CMood</td>
<td>0.44</td>
<td>3.86</td>
<td>0.000</td>
</tr>
</tbody>
</table>

\(R^2 = 0.20; \text{ adj. } R^2 = 0.18; F_{1,62} = 14.91; \ p = 0.000.\)

### Table 6
Results of hypothesis 3a and 3b

<table>
<thead>
<tr>
<th>Uncertainty level</th>
<th>BIU</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(U_1) (low)</td>
<td>4.96</td>
<td>1.09</td>
</tr>
<tr>
<td>(U_2) (high)</td>
<td>4.76</td>
<td>1.33</td>
</tr>
</tbody>
</table>

d.f. = 69, \(t\)-Stat = 0.70, \(p = 0.24\) (one tail).

### Table 7
Results of hypothesis 4

<table>
<thead>
<tr>
<th>Uncertainty level</th>
<th>(BIU = b_0 + b_1 CMood)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(b)-Value</td>
</tr>
<tr>
<td>(U_1) (low)</td>
<td>0.49</td>
</tr>
<tr>
<td>(U_2) (high)</td>
<td>0.44</td>
</tr>
</tbody>
</table>

\(t = 0.20; \ p = 0.84.\)
regression coefficients recommended by Cohen and Cohen showed that there was no significant difference between the regression coefficients ($b_{U1} = 0.49$, $b_{U2} = 0.44$, $t = 0.20$, $p = 0.84$). These results support hypothesis 4b but not 4a, consistent with Hypothesis 3. Thus, these results indicate that there was no discrepancy between the effects of induced and naturally occurring positive mood (Table 7).

6. Discussion and conclusion

We found that positive mood had an influence on intention to use a computerized decision aid and that the effects of positive mood did not depend on whether the positive mood was induced or natural. Contrary to our expectation following the AIM, the result did not show more favorable acceptance under higher levels of uncertainty. Consistent with what we expected due to positive mood theory, the positive mood effects did not differ across uncertainty levels.

To assess further which theoretical lens best explained our results, we compared the positive mood treatment with the control group using two post hoc analyses. The time used to complete the task did not show a difference between the control group and the positive mood treatment. This $t$-test does not reveal whether people in positive mood differ from their control counterparts in their effective use of the decision aid to learn the task. Therefore we conducted a second post hoc analysis. This analysis showed that there was no significant difference between the $G$ value for the mood treatment and for the control group, where $G$ captures the knowledge of the requirements of the task and the ability to apply that knowledge to predicting the criteria. These results suggest that subjects in the positive mood treatment made use of the external data at least as much as did the control group – a result more aligned with the argument of the positive mood theory than AIM. The lack of support for the hypotheses of stronger effects for higher uncertainty levels also indicated better alignment of our results with positive mood theory.

From a perspective of MIS technology acceptance research, our results provide support for establishing positive mood as a variable that influences acceptance. Apparently, positive mood effects are present whether or not they are induced in the research. In addition, our results suggest that new theoretical models of acceptance are needed to combine positive mood theory with the theories of reasoned action, etc.

Our experimental results suggest that a significant increase in uncertainty does not diminish the enhancing effects of positive mood on acceptance. Since today’s business environment is characterized by uncertainty, this suggests that organizations may benefit from the presence of positive mood when introducing a new IT. Our study has other practical implications: there will be significant improvement in intention to use due to a positive mood. This therefore provides managers with a way for increasing acceptance of a new system by paying attention to the mood of their employees by providing a pleasant work environment or fostering a positive organizational climate. Since positive mood is common, organizations may merely need to sustain the natural positive mood, rather than attempt to induce it.

The generalizability of the results is, however, limited by the laboratory setting of the experiment. Our experiment involved only one decision aid and thus generalizing the results requires more experimentation with different types of IT.

References


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