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Cognitive Feedforward and Feedback as Substitutes for Conscientiousness

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Abstract:
In this study, we explore the impact of feedback, feedforward, and personality on computer-mediated behavior change. We studied the impacts of the effects using subjects who entered information relevant to their diet and exercise into a database through an online tool. We divided the subjects into four experimental groups: those who received only feedback, those who received only feedforward, those who received both feedback and feedforward, and those who received neither feedback nor feedforward. We found that both feedforward and feedback impacted behavior change but that the effect was much greater for individuals who ranked low in conscientiousness than for individuals who ranked high in conscientiousness. In fact, the magnitude of the effect of feedforward and feedback was nearly the same as the magnitude of the effect of conscientiousness.

Keywords: Behavior Change, Decision Support Systems, Feedforward, Feedback, Conscientiousness.

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1 Introduction

Information plays an important role in influencing decisions, which involve a tradeoff between short-term versus long-term rewards. When evaluating whether or not to make a decision that will provide some payoff at a later date, a decision maker (DM) has to weigh the value of that future payoff against the short-term cost of that decision. An investor must weigh money’s present value against its future value. A student must weigh the benefit of gaining knowledge in the long term versus the value of leisure time in the short term. A health conscious person must weigh the future benefits of exercise and healthy eating habits against the instant gratification that comes from spending time watching a movie or eating ice cream. Research has found that individuals often give delayed gratification lower preference than immediate gratification when evaluating decision outcomes (Mischel & Ebbesen, 1970). Research has shown, however, that information presented to DMs when they make a decision can affect their preference for short-term versus long-term gains. For example, the manner in which a given outcome is framed (Loewenstein, 1988), the presentation of visual cues that demonstrate the value of future outcomes (Ebert & Prelect, 2007), and the provision of knowledge regarding the present value of future outcomes (Matsumoto, Peecher, & Rich, 2000) all affect preference for short-term versus long-term gains.

In particular, information can help make future rewards more salient to a DM. For example, people who see their credit card balance every time they make a purchase may not use their credit cards as much. Similarly, customers of an electric company may decrease the amount of electricity they use if they receive a projection of their electric bill based on current use each month. And overweight people may change their eating habits if someone makes the future effects of their eating and exercise habits clear to them every day. Salience has relevance in the business world as well since the manner in which information is presented plays a big role in influencing employees’ decisions to act in accordance with organizational goals.

Prior research has shown that information provided in the form of feedback and feedforward is effective in making decision outcomes more salient to DMs (Chenoweth, Dowling, & St. Louis, 2004; Montazemi, Wang, Nainar, & Bart, 1996; Singh & Singh, 1997). Feedforward is information provided to individuals before they make a decision. It can either suggest an action to take, explain how to take an action, or predict what the likely future outcome of an action will be. Feedback is information provided after a decision has been made. It explains what actions were taken in the past and identifies the outcomes associated with those actions. As their names imply, feedback focuses on past actions and their consequences, while feedforward focuses on future actions and their consequences (Dhaliwal & Benbasat, 1996).

This study extends previous findings on the effects of feedforward and feedback on decisions in two ways: 1) it examines the effects of feedforward and feedback on decisions involving delayed gratification, and 2) it studies the extent to which the impact of feedforward and feedback varies depending on the recipient of the information. Prior research has shown that individuals respond differently to information technology based on several different characteristics (Nass, Moon, Fogg, Reeves, & Dryer, 1995), which has led to efforts in various disciplines to tailor information to specific individuals as opposed to using a “one-size-fits-all” approach (Guelman, Guillén, & Pérez-Marín, 2015).

In this study, we examine the impacts of feedforward and feedback on decisions involving delayed gratification. While we believe that both feedforward and feedback will have similar effects on behavior, we keep them as separate constructs for two reasons: 1) we are interested in knowing whether the magnitude of the effect of feedforward will be greater than the effect of feedback, and 2) the concepts are fundamentally different and could have different effects on behavioral decisions. Feedback only provides information on a decision maker’s present state given the actions that the individual has taken thus far. Feedforward provides information about the future state of a decision maker should the individual take some specific actions. Prior research has shown that feedforward generally has a greater impact on future behavior than feedback (Björkman, 1972; Chenoweth et al., 2004; Montazemi et al., 1996; Singh & Singh, 1997), which one can expect since the mechanism by which both forms of information should work make the future outcomes more salient to the decision maker.

The context of this study involves decisions related to food consumption. We selected food consumption decisions because: 1) immediate decisions about eating and exercising have future impacts on weight loss and health, 2) there is a trade-off between the immediate cost of exercising and not eating and the future benefit of weight loss and better health, and 3) it is possible to conduct an experiment to observe whether providing feedback and feedforward causes dieters to reevaluate the trade-off between the costs
and benefits of exercising and eating less. We also believe that one can extend results found for food consumption decisions to other decisions.

To study the effects of cognitive feedforward and cognitive feedback on food-consumption decisions, we designed an application to provide people with information regarding their weight-management behavior. The application allowed people to enter in the amount and type of food they consumed each day and the amount and type of physical activity in which they engaged each day. The application then provided information (in the form of feedforward, feedback, both, or neither depending on the individual’s experimental group) to the individual regarding their decisions.

Because all humans differ, different types of information will likely affect them differently. Conscientiousness is a factor that one can expect to moderate the effect of feedback and feedforward on diet and exercise behavior. That is, people who are very conscientious may not need either feedback or feedforward to maintain a diet or exercise regimen, whereas people who are less conscientious may benefit greatly from feedback and feedforward.

This paper proceeds as follows. In Section 2, we review the literature on human behavior and decision making. In Sections 3 and 4, we discuss the study design and present the results, respectively. In Sections 5 and 6, we examine the implications of the results and the conclusions that one can draw from them, respectively. In Section 7, we end the paper by pointing out opportunities for future research to build on our results.

2 Literature Review

To develop our hypotheses, we drew on literature in the areas of decision support, psychology, and human-computer interaction. In this section, we discuss the results of studies that are relevant to our investigation of whether feedback and feedforward can substitute for conscientiousness. Figure 1 depicts the conceptual model we test this study. This conceptual model shows that feedback, feedforward, and conscientiousness directly affects decision outcomes and that conscientiousness moderates the effects of both feedforward and feedback on decision outcomes.

![Figure 1. Conceptual Model](image)

2.1 Decisional Guidance

The impact of information on decisions has been an area of interest in research on decision support systems for many years. Since the late 1970s, researchers have recognized the importance of change
agency in decision support systems (Silver, 1990). Silver discusses two types of change (i.e., directed and non-directed change) whose purpose can be served by implementing a decision support system. He also established different strategies for implementing systems intended to serve both purposes. Directed change, as Silver defines it, is change that occurs when the designers of a DSS know that a change will occur and deliberately force its direction. Non-directed change occurs when the designers of a DSS know that change will occur but do not attempt to influence the direction of the change.

In a later paper, Silver (1991) establishes a unified approach intended for studies that deal with influencing behavior using decision support systems. He defines decisional guidance as the manner in which a system influences its users’ decisions. Silver points out that there are two kinds of decisional guidance: inadvertent and deliberate decisional guidance. He also presents a typology of deliberate decisional guidance, which suggests that there are targets, forms, and modes of guidance. Targets involve the end goal of the guidance (whether to aid in structuring a decision or executing one). He categorizes forms as suggestive guidance or informative guidance. Suggestive guidance provides one with recommendations on what type of decision should be made, whereas informative guidance provides relevant inputs that may help one to make a decision but do not provide any specific recommendations.

Non-directed change and informative guidance offer a safe approach to influencing behavioral decisions. This type of guidance puts less responsibility on the DSS designer while allowing the system to serve its function of providing the information necessary to make an important decision. Some research suggests that informative guidance is more effective for making decisions about complex tasks than suggestive guidance (Chenoweth et al., 2004; Montazemi et al., 1996).

2.2 Feedforward and Feedback

Decision support systems can offer non-directed, informative guidance in the form of feedforward and feedback. Limayem and DeSanctis (2000) discuss the relationship between informative guidance and feedforward and feedback in detail. Feedforward is “generalized information pertaining to the input cues of an analysis that is provided to users prior to the performance of an analysis” (Dhaliwal & Benbasat, 1996, p. 348). In our food-consumption example, we told participants that, if they consumed X calories and burned Y calories for a certain time period, they would lose/gain Z pounds.

One presents feedback after an individual has made a decision. It is “knowledge of results” (Björkman, 1972, p. 152). Some evidence suggests that feedback alone may not result in better decisions (Sterman, 1989). The argument is that “the information content of outcome feedback is inadequate for decision makers to form a suitable model of the system” (Sengupta & Abdel-Hamid, 1993, p. 412), which is especially true for complex tasks where decision makers can find many reasons for why their decisions failed. In our food-consumption context, subjects would find it easy to rationalize that their weight gain resulted not because they ate too much or exercised too little but rather because they were stressed, their metabolism was off, or they ate at the wrong time. Rationalizing can make feedback be less effective than feedforward (Björkman, 1972; Chenoweth et al., 2004; Montazemi et al., 1996; Singh & Singh, 1997).

Because both feedforward and feedback provide task information, they are likely to make decision outcomes more salient. In our food-consumption example, making explicit the benefits that decision makers can gain from the additional effort necessary to diet and exercise should influence them to adopt behaviors that will have better long-term benefits as opposed to behaviors with less beneficial short-term results.

2.3 Effort vs. Accuracy

The decision support literature has used the concept of effort versus accuracy to understand how individuals formulate strategies to make decisions. The basic notion is that individuals will weigh the benefits they expect to gain from using any decision strategy against the costs of using, formulating, and implementing the strategy (Benbasat & Todd, 1996). Individuals often choose strategies that involve less effort. In order to determine whether improved accuracy compensates for invested effort, decision makers must receive feedback regarding their decision outcomes (Te’eni, 1991). Chenoweth et al. (2004) and Montazemi et al. (1996) extended the decision support literature on effort versus accuracy by showing that the salience of decision outcomes also is a factor in determining whether or not individuals decide to adopt a given decision strategy.

Individuals are more likely to invest effort in strategies when the outcomes of those efforts are made more salient due to individuals’ often discounting the future. That is, effort expended today affects a person
today, but the expected benefits from that effort do not affect a person until some time in the future. Therefore, unless the future benefits are made more salient, individuals are likely to avoid any strategy that requires more effort.

One can apply this concept to decisions related to individual behaviors. Systems that can make the future outcomes of behavior decisions clear to a person are more likely to influence behavior than those that do not. Saliency is especially relevant in healthcare, where most individuals become unhealthy by engaging in behavior that benefits them in the short term (e.g., drinking, smoking, poor diet) while discounting longer-term effects such as heart disease, lung disease, liver disease, and diabetes. Discounting future dangers leads individuals to ignore many public health warnings because they think that what may affect them in the future is not important in the present. Only when individuals face immediate consequences of their behavior do they tend to actually change it, such as a case where the presence of an impending epidemic kills in a matter of days rather than over a period of years or decades.

2.4 Computers as Social Actors

Although prior research has shown that feedback and feedforward can influence individual decisions by making outcomes more salient, no research has shown how feedforward and feedback affect different individuals in different ways. The Computers as Social Actors (CASA) paradigm states that social rules that apply to interactions between humans also apply to interactions between humans and computers (Nass et al., 1995). Because all humans differ, different types of information will likely have different effects on different people. In this study, we measured the effects of feedforward and feedback for people with different personalities. Although there is some controversy in this area, many agree that five distinct factors encompass human personalities. In this paper, we focus particularly on conscientiousness.

2.5 Conscientiousness

Conscientiousness is a high predictor of success in goal-setting situations. Individuals who rank high in conscientiousness tend to be dependable, persistent, organized, thorough, and reliable (McCrae & Costa, 1987; Tupes & Cristal, 1992; Goldberg, 1993; Booth-Kewley & Vickers, 1994; Roberts, Chernyshenko, Stark, & Goldberg, 2005a). Prior research has shown that individuals who rank high in conscientiousness are more likely to set and achieve higher goals (McCrae & Costa, 1987), adhere to wellness behaviors (Booth-Kewley & Vickers, 1994; Courneya & Hellsten, 1998; Conner & Abraham, 2001; Bogg & Roberts, 2004; Hill & Roberts, 2011), engage in protective health behaviors (Booth-Kewley & Vickers, 1994; Conner & Abraham, 2001; Roberts, Walton, & Bogg, 2005b), achieve higher levels of education (Hampson, Goldberg, Vogt, & Dubanoski, 2007), have greater career success through job performance (Judge, Higgins, Thoreson, & Barrick, 1999), and have more success with exercise regimens and other programs intended to modify individual health behaviors (Courneya & Hellsten, 1998).

Researchers have developed measures of conscientiousness in concert with measures of personality (Goldberg, 1990). One can define personality by distinguishable adjectives and their bipolar counterparts, and theorists have constructed expansive lexical lists. Beginning with tens of thousands of factors, researchers narrowed down the number of relevant personality factors to five by observing correlations, clustering, and factor analyses generated from self-reports and peer ratings (Thurstone, 1934; Cattell, 1943; Allport & Odbert, 1936; Norman, 1967; Goldberg, 1990). The psychological community has deemed this five-factor model (often referred to as the “big five”) a “reasonable representation of the human personality” (McCrae & Costa, 1987; Goldberg, 1990). The big five personality dimensions are: 1) extraversion, 2) agreeableness, 3) conscientiousness, 4) neuroticism, and 5) openness (McCrae & Costa, 1987; John, 1989).

Research has recognized conscientiousness as one of the more significant traits among the big five personality traits (Booth-Kewley & Vickers, 1994; Roberts et al., 2005a). Because research indicates that conscientiousness is a high predictor of success in goal-setting situations, we examine whether feedback and feedforward can help individuals who rank low in conscientiousness achieve success similar to those who rank high in conscientiousness.

3 Study Design

This study explores the impact of feedforward, feedback, and conscientiousness on calories consumed per day. Because research has shown feedback and feedforward make the outcomes of a given behavior more salient and because it has shown that making outcomes more salient to an individual affects that
individual’s decision making, we hypothesize that feedback and feedforward will reduce the average number of calories consumed per day. We also hypothesize that the combined effect of receiving both feedback and feedforward will be greater than the sum of the individual effects.

**H1:** Feedback reduces the number of calories an individual consumes per day (i.e., feedback has a negative effect on the number of calories an individual consumes per day).

**H2:** Feedforward reduces the number of calories an individual consumes per day (i.e., feedforward has a negative effect on the number of calories an individual consumes per day).

**H3:** Feedback more heavily reduces the number of calories an individual consumes per day when feedforward is present (i.e., there is an interaction effect between feedback and feedforward).

Prior research has shown that individuals who rank high in conscientiousness are more likely to follow an exercise regimen and are much less likely to indicate that frequently mentioned barriers to exercise affect them personally (Courneya & Hellsten, 1998). Therefore, we expect to find that conscientiousness will reduce the number of calories individuals consume per day.

**H4:** Conscientiousness reduces the number of calories an individual consumes per day (i.e., conscientiousness has a negative effect on the number of calories an individual consumes per day).

Factors that relate to exercise behavior also will likely relate to weight management because they require similar effort. Since behavior change concerns overcoming barriers, we hypothesize that conscientiousness will moderate the effect of feedback and feedforward on behavior change. Specifically, feedback and feedforward will more likely influence individuals who rank low on conscientiousness scales than those who do not. We reason that, if individuals have personality types that predispose them to engage in positive health behaviors, then efforts to influence those individuals using feedback and feedforward may not have much of an effect. However, if individuals struggle to engage in positive health behaviors, then feedback and feedforward may push them to overcome perceived barriers. That is, where one has little room for improvement, feedback and feedforward are less likely to have an effect than when one has more room for improvement. For this reason, we hypothesize that feedback and feedforward will have a smaller effect on individuals who rank high in conscientiousness than on those who rank low in conscientiousness.

**H5:** The magnitude of the reduction in the number of calories consumed due to receiving feedback is greater for low-conscientiousness subjects than for high conscientiousness subjects (i.e., there is a two-way interaction between feedback and conscientiousness).

**H6:** The magnitude of the reduction in the number of calories consumed due to receiving feedforward is greater for low-conscientiousness subjects than for high conscientiousness subjects (i.e., there is a two-way interaction between feedforward and conscientiousness).

**H7:** The interaction between feedforward and feedback is greater for individuals with low conscientiousness (i.e., there is a three-way interaction between feedback, feedforward, and conscientiousness).

### 3.1 Online Weight and Physical Activity Management Application (OWPAMA)

To test these hypotheses, we conducted an experiment on different groups of individuals. The experiment involved recruiting individuals to use an online weight- and physical activity-management application (OWPAMA). This application, as its name suggests, aids individuals in managing their weight and physical activity—the conditions in question.

We developed the application using our own labor and money specifically for the experiment. It is a Web-based application that resides on a commercial hosting platform on a Linux server. We developed the program using PHP, HTML, and Javascript. The data the application used resided on a MySQL database server that, in turn, resided on a commercial hosting platform. We designed the application to work with a Web browser. Although one could easily access the application through a browser on a mobile device, no mobile app was available to access the program. We provided individuals with a link to the website on which the application resided that asked them to register to use the application.
As part of the registration process, we asked participants to complete a personality questionnaire based on the big five inventory survey (Goldberg, 1993). We used the responses to these questions to score participants on their level of conscientiousness. After registering, we randomly placed individuals into one of four experimental groups: those who received feedforward only, those who received feedback only, those who received both feedforward and feedback, and those who received neither feedforward nor feedback.

Once registered, we asked participants to log their diet and physical activity into the system each day. Participants could go back and complete information for a day that had already passed if their schedules kept them from being able to log in and complete entries on a specific day. The application featured a preloaded list of foods with assigned calories, which came from the USDA National Nutrient Database for Standard Reference, Release 21 (Gebhardt et al., 2008). Participants could enter search terms for foods that they had eaten during the day and select from a list of foods in the prepopulated database. In this way, they could easily count the calories they consumed. If participants could not find foods they had eaten in the USDA database, they could enter foods on their own provided that they had calorie information. We designed the application in such a way that participants could easily copy all entries from a previous day and also select quickly from a list of foods they entered frequently. Figure 2 shows a
screenshot of the calorie-consumption screen. Once participants entered the food types and quantities into the application, it calculated the number of calories they consumed.

**Figure 3. OWPAMA Activity Log**

In pretesting the system, we learned about the importance of ease of use. For instance, we incorporated dropdown lists that allowed participants to easily copy all entries from a previous day (both foods and activities) and select quickly from a list of foods or activities that they entered frequently. This feature contributed greatly to participants’ satisfaction and continuity.

Candidates for recruitment to the study were individuals who wished to increase their physical activity and decrease their weight. All individuals who participated in the study answered questions regarding their current weight, diet, physical activity, and other relevant statistics (e.g., height, which we used to calculate their BMI). After entering calorie consumption and activity data, the system would then provide the subjects with information tailored to each experimental group.

We gave individuals in the control group only descriptive information about the number of calories they consumed and the number of calories they burned in the current day and during the total time since they began the program. We augmented this descriptive information for individuals in the other groups. We gave individuals in the feedback-only group additional information about their calorie deficit/surplus for the current day and their cumulative calorie deficit/surplus since beginning the program. We gave individuals in the feedforward-only group additional information about where their current-day calorie deficit/surplus
would place them with respect to their weight loss goals in 1 month, 3 months, and 6 months and where their cumulative calorie deficit/surplus would place them for the same time periods. We gave individuals in the feedforward and feedback group all of the information that the other groups received. Table 1 summarizes the descriptive, feedback, and feedforward information. Table 2 summarizes which information we gave to which individuals.

<table>
<thead>
<tr>
<th>Information type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Descriptive</td>
<td>The number of calories consumed and burned for the current day as well as since the program began.</td>
</tr>
<tr>
<td>Feedback</td>
<td>The subject's calorie differential (number of calories consumed minus number of calories burned) for the current day and since the program began.</td>
</tr>
<tr>
<td>Feedforward</td>
<td>The subject's projected weight loss/gain if he/she continues the current day's pattern, as well as the subject's projected weight loss if the overall pattern since beginning the program is continued.</td>
</tr>
</tbody>
</table>

Table 2. Experimental Groups

<table>
<thead>
<tr>
<th>Experimental group</th>
<th>Descriptive</th>
<th>Feedback</th>
<th>Feedforward</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control group</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Feedback only</td>
<td>✓ ✓</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Feedforward only</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Feedforward and feedback</td>
<td>✓ ✓ ✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

We asked individuals to participate in the study for at least 30 days. The study took place over the course of a six-month period.

4 Results

We recruited participants to participate in the study via email and social media. We recruited the majority (90 percent) of the subjects from graduate student associations from universities in the United States. We entered the term “graduate student association” into Google from which we identified associations at 58 different universities. We sent communications to each of these associations with a request to send emails to their members that explained the purpose of the study and asked them to participate in the study. We could not determine exactly how many graduate students we invited to participate, but 176 students agreed to participate in the study.

We recruited a further 19 subjects from one of the author’s Facebook friends. This author invited these individuals to participate in the study and asked them to invite their own friends to participate in the study. Because we do not know how many friends each friend of the author had, we could not determine how many Facebook related requests for participation the author sent.

We told participants that they would be participating in a study that involved using a computer application used to track calories consumed and daily activity in order to help them manage their weight and exercise activities. We collected data from 195 subjects over a six-month period. Sixty-four subjects chose to withdraw from the study before completion. Another 82 subjects did not provide information on caloric intake and physical activity for at least seven different days during the study period. As a result, 49 subjects with which to conduct an analysis remained. Table 3 shows a breakdown of the number of finishers and dropouts and the groups to which they were assigned.

Table 4 shows the participants demographic makeup. Overall, 76 percent of participants were female, which was nearly identical for finishers and dropouts. The average age of the dropouts was slightly lower than the average age of the finishers (30 years versus 32 years). Moreover, the difference between the average age of the dropouts and the finishers was greater for males than females, which suggests young males may be less concerned about weight loss than young females.
Table 3. Finisher/Dropout Cell Sizes

<table>
<thead>
<tr>
<th>Experimental group</th>
<th>Finishers</th>
<th>Dropouts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control group</td>
<td>9</td>
<td>41</td>
</tr>
<tr>
<td>Feedback only</td>
<td>13</td>
<td>35</td>
</tr>
<tr>
<td>Feedforward only</td>
<td>11</td>
<td>35</td>
</tr>
<tr>
<td>Feedforward and feedback</td>
<td>16</td>
<td>35</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>49</strong></td>
<td><strong>146</strong></td>
</tr>
</tbody>
</table>

Table 4. Finisher/Dropout Demographic Makeup

<table>
<thead>
<tr>
<th>Gender</th>
<th>Count</th>
<th>Average age</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Finishers</td>
<td>Dropouts</td>
</tr>
<tr>
<td></td>
<td>Finishers</td>
<td>Dropouts</td>
</tr>
<tr>
<td>Male</td>
<td>11</td>
<td>35</td>
</tr>
<tr>
<td>Female</td>
<td>38</td>
<td>111</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>49</strong></td>
<td><strong>146</strong></td>
</tr>
</tbody>
</table>

To measure changes in caloric intake, we plotted each person’s daily caloric intake over the course of the program against the day in the study to which the information applied. We plotted calories consumed on the vertical axis and day of the program (1, 2, … 180) on the horizontal axis. We used linear regression analysis to calculate the slope for the resulting line for each individual. This slope shows whether calories consumed tended to increase or decrease over the course of the program and represents the rate of change in calorie consumption per day. We used this rate of change as the dependent variable in a second regression analysis. Cohen, Cohen, West, how Aiken (2003) cover using rate-of-change as a dependent variable for analyzing the impact of independent variables on changes over time. Figure 4 provides an example of such a slope for one subject who participated in the program for 42 days.

![Calorie Trend Line](image-url)

*Figure 4. Plot of Daily Calories Consumed versus Day in Study*
We analyzed the effects of the variables of interest on the slope of caloric intake using linear regression. The slope represents the average change in the number of calories consumed by a person per day they participated in the study. To measure the effect of conscientiousness, we classified individuals as high conscientiousness or low conscientiousness depending on whether they fell above or below the median conscientiousness score for all subjects. We classified subjects in this manner because the effect of conscientiousness is likely to be nonlinear. We analyzed 49 observations in total. Table 5 shows the parameter estimates. The overall model was statistically significant at the .01 level.

Table 5. Regression Results for Calorie Consumption

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter estimate</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>60</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Feedforward</td>
<td>-76</td>
<td>.0002</td>
</tr>
<tr>
<td>Feedback</td>
<td>-47</td>
<td>.0097</td>
</tr>
<tr>
<td>Feedforward and feedback</td>
<td>63</td>
<td>.0121</td>
</tr>
<tr>
<td>High conscientiousness</td>
<td>-53</td>
<td>.0129</td>
</tr>
<tr>
<td>Feedforward * conscientiousness</td>
<td>66</td>
<td>.0207</td>
</tr>
<tr>
<td>Feedback * conscientiousness</td>
<td>20</td>
<td>.4635</td>
</tr>
<tr>
<td>Feedforward and feedback * consc</td>
<td>-27</td>
<td>.4581</td>
</tr>
</tbody>
</table>

With respect to main effects, Table 5 shows that feedforward, feedback, and conscientiousness all had the anticipated main effect on calorie consumption and were statistically significant at the .001, .01, and .05 levels, which supports H1, H2, and H4. However, instead of exceeding the sum of the individual main effects, the combined effect of feedback and feedforward was equal to slightly less than 50 percent of the sum of the main effects (-76 - 47 + 63 = -60). Because the interaction effect between feedforward and feedback was positive rather than negative as we hypothesized and was statistically significant at the .05 level, we must reject H3. It appears that receiving either feedback or feedforward is valuable but receiving both is not much better than receiving just one.

The magnitude of the point estimate for feedforward (-76) was quite a bit larger than the magnitude of the point estimate for feedback (-46), which indicates that feedforward has a larger effect on calories consumed than feedback. However, the upper and lower limits of the 95 percent confidence interval for the difference between the main effects of feedforward and feedback were -2.4 and 61.6, which includes zero. Although the observed 30 calorie difference in the magnitudes of the effects was not statistically significant, the fact that this confidence interval had a width of 64 indicates the low power of this test. A power analysis shows that, if the two effects differed by as much as 30 calories per day, the probability of rejecting the null hypothesis was only .45 with the current sample size. Thus, although the evidence indicates that feedforward had a greater impact than feedback, we need additional studies with more subjects to make a definitive statement about the magnitude of this difference.

With respect to interactions with conscientiousness, Table 5 shows that feedforward had the anticipated two-way interaction with conscientiousness. The estimate for the effect of feedforward on calorie consumption was 66 units greater for subjects with low conscientiousness than for subjects with high conscientiousness, and the interaction effect was statistically significant at the .05 level. This result supports H6. Interestingly, the impact of this interaction effect completely nullified the impact of conscientiousness. That is, after we provided feedforward, the difference in calorie consumption between individuals with high and low conscientiousness was not statistically significant. The model actually indicates that, after we provided feedforward, individuals with low conscientiousness did slightly better than individuals with high conscientiousness (60 - 76 = -16 versus 60 - 76 - 53 + 66 = -3), but this difference was not statistically significant.

Feedback also had the anticipated two-way interaction with conscientiousness. The magnitude of the interaction effect for feedback and conscientiousness was a positive 20 but not statistically significant. Thus, while we found support for H5, it was not statistically significant. Lastly, the estimate for the three-way interaction among feedforward, feedback, and conscientiousness was -27 and not statistically significant. Because the coefficient was not significant and because the sign of the coefficient was negative, we did not find support for H7.
Figures 5, 6, and 7 graphically illustrate the results presented in Table 5. These figures plot the expected values of the dependent variable (average change in number of calories consumed per day) for a selected subgroups of subjects. These figures show that individuals with high conscientiousness did not benefit very much from receiving feedforward, feedback, or both. However, individuals with low conscientiousness benefitted a great deal from receiving either feedforward or feedback, and the receipt of feedforward, feedback, or both enabled individuals with low conscientiousness to perform as well as individuals with high conscientiousness with respect to reducing the number of calories consumed.
Figure 7. Control versus Feedforward and Feedback

Note that: 1) the main effects for feedforward and feedback had the same sign, 2) the 95 percent confidence interval for the difference in the magnitudes of the main effects for feedforward and feedback included 0, 3) the two-way interaction effects of feedforward and feedback with conscientiousness had the same sign, and 4) the 95 percent confidence interval for the difference in the magnitudes of the two-way interaction effects of feedforward and feedback with conscientiousness included 0. Due to these results, we ran our analysis again using only two binary variables: low conscientiousness versus high conscientiousness and did not receive any feedback versus received feedforward, feedback, or both.

We also combined the subjects that received only feedback, only feedforward, and both feedforward and feedback into one group because, given how we presented the information to the subjects (see the screenshots presented in Figure 8), they could easily approximate the feedforward information given the feedback information. The approximation would not be as precise as the feedforward information that the application provided, but the implications for future weight loss would be clear. Table 6 presents the results, and Figure 9 graphically illustrates them.

The implications of Table 6 and Figure 9 are the same as those of Table 5 and Figures 5, 6, and 7. They show that, in the absence of feedforward or feedback, people that scored low on conscientiousness increased their calorie consumption much more than persons that scored high on conscientiousness (60 vs. 60 - 53 = 7, respectively). However, if people who scored low on conscientiousness received feedforward, feedback, or both, then the change in their calorie consumption was nearly the same as that of persons that scored high on conscientiousness (60 - 60 = 0 versus 60 - 53 - 60 + 49 = -4). This finding is important for anyone who wants to design a program intended to modify one’s behavior.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>60</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>High Conscientiousness</td>
<td>-53</td>
<td>.0141</td>
</tr>
<tr>
<td>Feedforward, Feedback, or Both</td>
<td>-60</td>
<td>.0003</td>
</tr>
<tr>
<td>(Feedforward, Feedback, or Both) * Conscientiousness</td>
<td>49</td>
<td>.0368</td>
</tr>
</tbody>
</table>
Discussion

The results suggest that providing feedback and feedforward can act as a substitute for conscientiousness. Individuals who are more conscientious tend to make decisions that are in line with consuming fewer calories. Lower conscientious individuals tend not to make these decisions unless they receive feedback and feedforward when making them, which suggests that one can overcome the effect of a person’s personality on their tendencies to make decisions by presenting them with information that
makes the outcome of their decision choice more salient (i.e., feedback and feedforward help those who are most in need of an intervention). The ability of feedforward and feedback to substitute for low conscientiousness has implications beyond the type of decisions that we studied here. These results are relevant to all employers who wish to align employees’ decisions with corporate interests. Several studies show that conscientious individuals tend to pursue more conventional career paths (Albion & Fogarty, 2002), which implies that efforts to provide information to influence decisions may be especially important for employees in less conventional career areas where the outcomes of the decisions may be the most important. Knowledge of how conscientiousness and feedforward/feedback interact also helps to explain why some efforts at providing information to influence decisions succeed and others fail.

One seemingly counterintuitive result of our study is that, in the absence of feedback, both individuals that scored low on conscientiousness and individuals that scored high on conscientiousness tended to increase their daily calorie consumption. Given that the individuals were trying to lose weight, this result seems surprising. One can explain it with the rationale that, while all individuals start a weight loss program with very good intentions, some become discouraged as time progresses. Indeed, we found that this tendency to become discouraged was more pronounced for persons with low conscientiousness (+60 calories per day on average) than persons with high conscientiousness (+7 calories per day on average). Moreover, the presence of feedforward, feedback, or both allows persons with low conscientiousness to stick to their diet (no increase in calorie consumption throughout the program), while persons with high conscientiousness can reduce their calorie consumption (a reduction of 3 calories per day on average throughout the program).

Our findings seem especially relevant in today’s world as compared to the pre-smartphone era. Due to the number of mobile applications available to people today, decision makers can receive informational guidance when making a decision much more quickly and frequently than in the past. Individuals can compile data from numerous sources, including wearables, sensors, and GPS data to provide instant feedback and feedforward regarding decisions and their potential outcomes. Understanding the effects of this instant guidance on various populations will become increasingly important as vendors design solutions intended to influence decisions in real time through mobile computing devices. Designers of these solutions must think about the elements of feedforward and feedback that are most effective at making the future benefits of a decision more salient and getting individuals to delay gratification.

6 Limitations

As with any study, ours has several limitations. First, we used self-reported data items. Because we had no way to validate anyone's responses to the big factor index questionnaire or entries of caloric intake, our results rely on subjects’ desire and ability to accurately report data. This limitation is common in behavioral research and likely only to have minimal impact on the results.

Second, the individuals who participated in this study did not come from identical environments. Some may have been students, some may have been working full time, some may have been unemployed, and so on. Many variables could affect an individual's ability to change their behavior, and we did not control for all such variables in this study. However, because of the recruitment methods we used, the majority of the students who participated in the study were likely to have been graduate students. Therefore, they likely had many similarities, and variations in lifestyle and location were unlikely to have impacted the results to any large extent.

Finally, we note that the small sample size resulted in wide confidence intervals for the effects that we found to be statistically significant and low power for testing whether the magnitudes of the effects of feedforward and feedback were significantly different. In order to obtain more precise estimates of the magnitudes of the effects and of the differences in the magnitudes of the effects, we need additional studies with more subjects.

7 Future Research

This study concerns influencing behaviors related to an individual's health. The findings suggest a relationship between personality type and feedforward and feedback in influencing health behaviors. This relationship will be more interesting and impactful if one can show it to be generalizable. That is, if other research finds the relationship in this paper to pertain to other types of behaviors, it will aid in the design of
a wide variety decision support systems. Our findings could also help to explore and explain why many decision support systems have failed in the past.

One example of a potential behavior in which one could explore this relationship would be personal finance. Similar to weight-change behavior, managing personal finance involves calculations that are relatively straightforward. Individuals can easily determine how much they can afford to spend each month based on income just as they can easily determine how much they can eat each day based on the amount of calories burned each day. However, certain expenses always come up for which the immediate effects of spending may be difficult to see. Feedforward and feedback have the potential to make the outcomes of such purchases more salient by allowing the purchaser to see the effects of spending habits on the outcomes of specific financial goals. Based on our findings of, the effects of feedback and feedforward would likely be higher for individuals with low conscientiousness in personal finance decisions than for individuals with high conscientiousness. Future studies could confirm this relationship. Studies that yield results similar to ours would suggest that one can generalize the results to a broader range of behaviors. A finding that reveals different results may lead to further questions about the differences between weight-management behavior and personal finance behavior. Answering such questions could lead to broadened knowledge regarding the relationship between feedforward, feedback, personality, and behavior.

The outcome of interest in this paper is calorie intake, which relates to a decision to modify an existing behavior. The use of information to modify behavior could have implications in the business world for making changes to existing workflows or procedures. Studying the manner in which the effects of feedforward, feedback and personality types influence decisions to adopt new behaviors would also be interesting. In the context of this study, adding exercise to an existing routine rather than simply changing a diet would be an interesting extension along these lines. Other contexts that might be explored include: whether feedforward/feedback related to personal finance decisions would influence someone’s decision to bring in more income rather than adjusting spending habits and whether feedforward/feedback regarding the efficiency of a specific process could lead to one’s adopting new technology to make the process more efficient rather than re-tooling the existing process with available technology.

Finally, we believe that the non-significant difference between the impact of feedforward and feedback in this study resulted from the form of feedback used rather than a true equality of the two types of information. A future study that provides feedforward in a stronger form than we provided might show a statistically significant difference between the two.
References


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