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Self-Experiments and Analytical Relapse Prevention

Farrokh Alemi, PhD; Shirley Moore, PhD; Heibatollah Baghi, PhD

Patients give many reasons for why they have not kept up with their resolutions; research shows that many of these causal attributions are wrong. This article provides a tool to help patients sort out causes of and constraints on their behavior, in general, and exercise, in particular. Patient's diary data can be analyzed to flag erroneous causal attributions, and thus assist patients to understand their behavior. To start the diary, the clinician works with the patient to assemble a list of possible causes. Using the list, a diary is organized that tracks the occurrences of various causes and the target behavior. At the end of 2 to 3 weeks, the diary data is analyzed using conditional probability models, causal Bayesian networks or logistic regression. A key issue in the analysis of diary data is to separate out the effect of various causes. Typically, causes co-occur, making it difficult to understand their independent effects. Another problem with analysis of diary data is the small size of the data. This article shows how small longitudinal data from patient diaries can be analyzed. The analysis may refute or support causes hypothesized by the client. The patient uses the insights gained from the diary analysis to prevent relapse to unhealthy behaviors. The process is continued for several cycles of organizing, keeping, and analyzing the diary data. In each cycle, the patient gains new insights and makes additional attempts to create a positive environment that allows him or her to succeed even if his or her motivation waivers. This article provides details of how diary data can be analyzed to help patients make correct causal attributions.

Key words: *artificial intelligence, Bayesian networks, diary, lifestyle management, machine learning, personal improvement, relapse prevention*

When clients want to change, occasionally they fail and relapse into old habits. In these circumstances, it is important to understand causes of relapse so that clients can address the root cause of the problem. Often clients focus on their motivation and not on the events and routines that have lead to the relapse. As a result, relapses reoccur and clients fail to maintain their new habits. This article is organized to improve understanding of root causes of relapse. It uses diary data to analyze potential causes of relapse; hence, we call the approach an "analytical relapse prevention."

Patients give many excuses for why they have not kept up with their exercise plans. Unfortunately, neither the clinicians nor the clients may know whether these excuses are true reasons for the client's behavior. Even if they are, neither one will know if they are the distal root causes of relapse or some obvious event that preceded relapse. Relapse prevention is widely practiced in substance abuse treatment, smoking cessation programs, treatment of depression, treatment of sexual dysfunctions, and many more behavioral disorders.[1–4] In almost all of these circumstances, the client has failed to keep up with his or her resolution. When asked, both the patient and the clinician are able to suggest possible causes. Many studies show that causal attributions can be fallacious.[5–7]

Author Affiliations: *Health Administration and Policy, George Mason University, Fairfax, Virginia (Dr Alemi); School of Nursing, Case Western Reserve University, Cleveland, Ohio (Dr Moore); and Department of Global and Community Health of College of Health and Human Services, George Mason University, Fairfax, Virginia (Dr Baghi).*

Corresponding Author: *Farrokh Alemi, PhD, Health Administration and Policy, George Mason University, 4400 University Dr, Fairfax, VA 22030 (falemi@gmu.edu).*

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The most egregious of these fallacies is a tendency to attribute successes to the client's skills/efforts and failures to events outside of the client's control.[8–10] Analytical relapse prevention checks the accuracy of causal attributions by the client. Investigation may reveal root causes that are surprisingly hidden and seemingly unrelated to the behavior. A client, for example, may fail to keep his or her resolution not to use drugs because his or her depression is not adequately controlled by antidepressant. In another example, a car pool might help a client reduce his or her junk food intake because he or she could get home earlier, and thus could prepare a meal. These are surprising causal effects, the relationship between these causes and their effects are not always self-apparent. Analytical relapse prevention is designed to reveal and check the validity of root causes of relapse.

The analysis starts with an audit of relapses. Clients list possible causes of relapse/success, including both constraints and promoters of the behavior. Then for the next 2 to 3 weeks, they maintain a diary and gather data on success and presence of various causes. After a period, the data are analyzed and compared with original conjectures about causes of relapse. Often the process helps the clients think through newer causes of relapse and start another 2 to 3 weeks of checking their validity. Through cycles of data collection and analysis, clients are expected to arrive at a more accurate understanding of their circumstances.

Some scientists have suggested that in order to better understand the impact of different causes on their success or failure, clients should use a full factorial experimental design.[11] This approach allows statisticians to estimate both the main and interaction effects for various combinations of causes. In this approach, the client conducts a series of experiments. Each experiment examines the impact of a different combination of the causes. Alemi and Alemi[12] point out that a full factorial design is not practical as it requires clients to continue their experimentation even after they have found initial success in one of the trials. Most clients would stop experimentation and repeat what seems to work. Because they do so, only a partial factorial design will be available and the main effects of causes may be confounded with higher-order interactions among the causes. Instead of having a design that will sort out the effect of various causes, clients collect observational data that are often correlated and difficult to analyze.

The problem is made more intractable because of the limited amount of data collected in a diary. For example, over 2 weeks of keeping an exercise diary, assuming that the client has been faithful and made an entry every day, there is a total of 14 data points from which we need to estimate a large number of parameters. When there are 3 causes, there are 3 main effects, 3 pair-wise interactions, and one 3-way interaction. This is a total of 7 parameters that must be estimated. With 4 causes, there are 4 main effects, 6 pair-wise interactions, four 3-way interactions, and one 4-way interaction. With 5 causes there are 5 main effects, 10 pair-wise interactions, ten 3-way interactions, five 4-way interactions, and one 5-way interaction. In general, if there are n causes and interactions of k causes are to be considered, then there are $n!/(n-k)!k!$ possible interactions. Obviously, when many causes are considered, the number of parameters that must be estimated often exceeds the number of data points available.

One way out of this shortage of data is to focus on estimating the main effects and ignore all interactions. But some interactions, in particular constraints on a cause, could completely change the situation. Ignoring these constraints will distort the estimated main effects of causes. For example, a cause leading to exercise is "planning to commute to work by biking." "Rain" might be a constraint on the impact of this cause, meaning the client will not bike to work if it is raining. Ignoring the impact of this constraint will not make sense, as rain does not reduce the impact of the decision to bike to work on exercise levels by a few points, it completely eliminates it. In this article, we show an algorithm that ignores most interactions but not the interactions between causes and constraints.

Traditional statistical methods (eg, analysis of variance) are not useful in the analysis of diary entries because there are many parameters to estimate and there are many potential associations among combination of causes. Instead, we rely on artificial intelligence and heuristic methods of learning from a small sample of cases. In particular, we rely on progress made in causal modeling and Bayesian networks to better understand diary data.[13,14] These approaches have the benefit that they allow discovery of main as well as interaction effects from small data sets.

DIARY FOR CAUSAL ANALYSIS

Figures 1 and 2 show a diary designed for monitoring causes and barriers to exercise. The diary has 2 pages: a daily page to capture what happened on a particular day, and a back page, half of which shows when looking at the daily page and lists possible

Day 1

__ __/__ __/__ __
D D / *M M* / *Y Y*

Did you exercise?
☐Yes ☐No ☐Not sure

Steps taken today: ? ? ?, ? ? ? ,? ? ?

Did you talk about exercise with others?
☐Yes, with friends or family members
☐Yes, with project staff ☐No

Start time of exercise:

__ __ : __ __
H H : *M M*

End time of exercise:

__ __ : __ __
H H : *M M*

Type of exercise:

Level of exertion:

☐Very, very light	☐Somewhat hard
☐Very light	☐Hard
☐ Light	☐Very hard
☐Fairly light	☐Very, very hard

Did you reach your prescribed exercise zone?
☐Yes ☐No ☐Not sure

Any changes in your medications?
☐Yes ☐No ☐Not sure

Any contact with health services?
☐Emergency Room ☐Office visit
☐Hospital

Was the contact heart related?
☐Yes ☐No

Check ☐ if present

☐
☐
☐
☐
☐
☐
☐
☐
☐
☐

Cut out this section

Figure 1. A sample daily diary page for exercise.

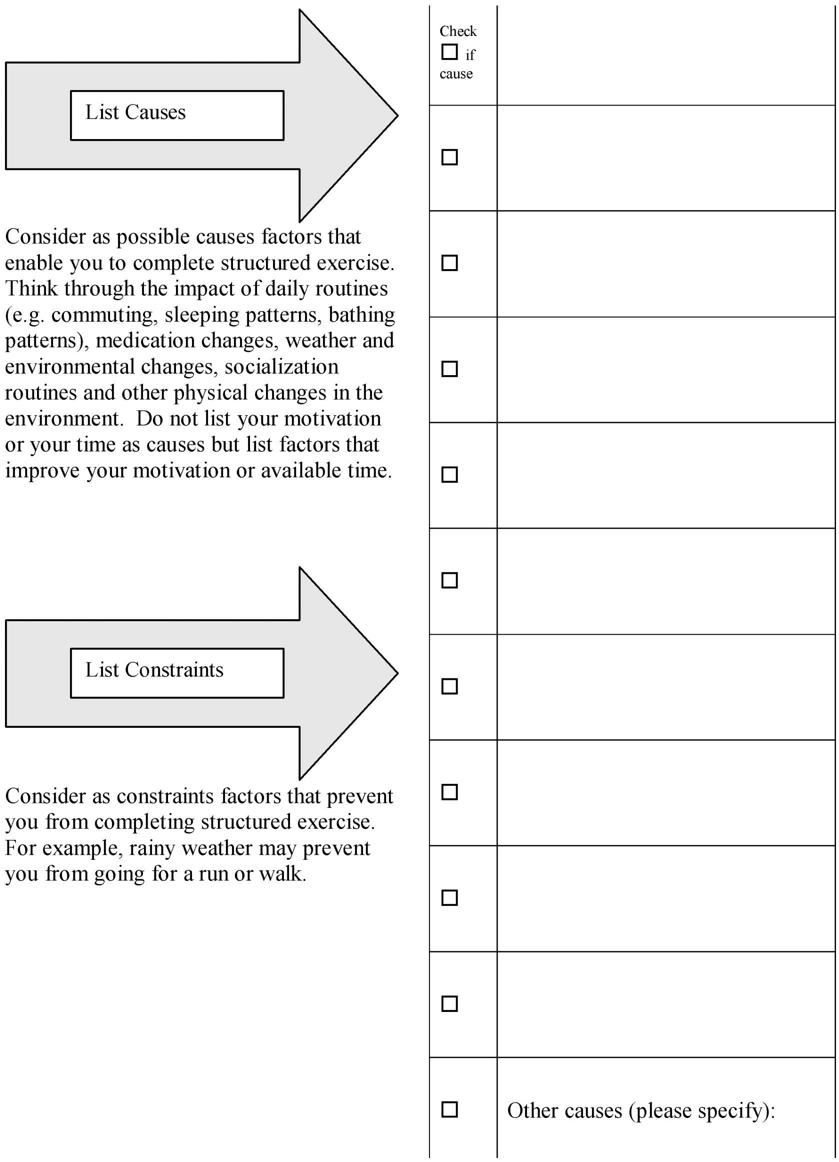

Figure 2. A sample diary back page for exercise.

causes imagined by the client. Figure 1 shows the daily page.

The back page includes an area to list various causes of his or her behavior. On the right of the page, the client can list the key causes he or she wants to monitor for the next 2 weeks. The creation of a list of causes to track is done prior to start of the diary entries. This section of the back page can be seen when looking at the daily page. Figure 2 shows a sample back page organized for listing causes of exercise.

The client uses the diary for 2 to 3 weeks to monitor the occurrences of causes listed in the back page. Once the diary is complete, the client mails it to his or her clinician who analyzes the data and returns it to the client. Repeated cycles of data collection and analysis allow the client and the clinician to understand what leads to success. This diary is in use in a current research project of Moore and Alemi.[15]

DEFINITION OF TERMS USED IN ANALYSIS OF DIARY DATA

Before we show how the diary data are analyzed, various terms and abbreviations need to be defined. Assume that a client has collected daily information about the presence of various causes X_i, Y_i, Z_i, ..., where X, Y, and Z show the cause and i indicates the day. The function X_i is 1 if the cause has occurred on day i, and 0 otherwise. Furthermore, suppose that we have also collected data on whether the client has failed or succeeded. Let the function S_{i} be 1 if the client has succeeded on day i, or 0 otherwise.

The probability of success given each cause is shown as $p(S \mid X)$, $p(S \mid Y)$, $p(S \mid Z)$, and so on. In this notation, the vertical bar is read as "given" and X means a situation where the cause X is present and no other cause is present ($X = 1$, $Y = 0$, $Z = 0, \ldots$). For ease of presentation, we have deleted the explicit indication that all other causes should be absent. $p(S \mid X)$ is not the same as $p(S \mid X, Y = ?, Z = ?, \ldots)$. The latter indicates the probability of success from cause X given that we know nothing about occurrence of other causes. The former shows the probability of success given that X has occurred and no other cause has occurred. The difference is that we know other causes have not occurred. When people talk of the impact of cause, they are thinking of $p(S \mid X)$, even though there maybe many causes which they are not aware of. Part of the problem of analyzing diary data is to separate the impact of cause X from all other causes. Statisticians typically refer to this as the main effect of the cause.

Examination of interactions between causes is important because of a special type of causes that we call constraints. When an event eliminates the impact of a cause, we refer to it as a constraint. The constraint by itself has no impact on success. For constraint Y, this is shown as:

$$p(S|Y) \approx 0$$

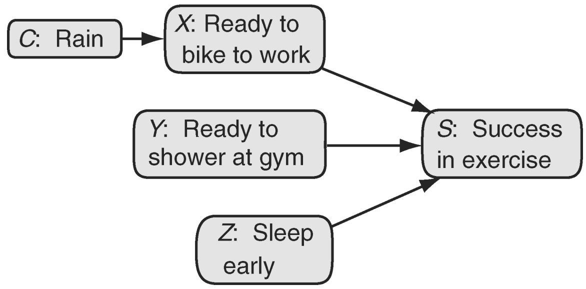

Figure 3. A causal diagram showing causes *X*, *Y*, and *Z* and constraint *C*.

In this equation, "$\approx$ 0" should be read as "is negligible or near zero." Constraints interact with causes in reducing the probability of success. If X is a cause and C is a constraint, we show this as:

$$p(S|X \text{ and not } C) > 0$$

$$p(S|X \text{ and } C) \approx 0$$

These 2 statements indicate that the impact of cause X on success is reduced to a negligible amount because of the presence of constraint C. A key task for analysis of diary data is to estimate the interactions among constraints and causes.

Figure 3 visually shows the main effects for the 3 causes X, Y, and Z and 1 constraint C. This figure shows a network linking causes to success. A causal model should not contain a loop, that is, it should not start from a node and follow the directions in the network and return to the same node. The network of relationships depicted in the figure does not include a loop. It shows how various causes and constraints affect the success rate. Each cause by itself is shown as a node. The arcs between any 2 nodes show the presence of an association. In this figure, no relationship is assumed between causes X, Y, and Z. The arrows show the direction of causality. The effect of X is shown as an arrow from the node X to the node S, the node marking success. The constraint C is assumed to affect the impact of cause X. In the graph, this is shown as a directed link between C and X. The numerical relationship between C and X (not shown in the graph) is specified so that presence of C eliminates consideration of X as a cause of success.

ANALYSIS OF DIARY DATA

Building a causal model requires learning the model structure and parameters from the diary data. Unfortunately, as mentioned earlier, diary data are limited. In most cases, patients are asked to collect information on factors that may change in 2 to 3 weeks. This yields between 14 and 21 data points, from which both the structure and the parameters of the Bayesian network, must be assessed. Heckerman et al[16] has shown that with a sample size of 500, significant errors in detecting the structure of Bayesian networks could occur. With a sample size of 14, a great deal more errors can occur.

To remedy the lack of data, we use a client's insight into the problem to guide the learning of Bayesian network structure. This is different from unguided machine learning typically done for learning structure of Bayesian networks.[17] To begin with, we know that causes lead to effect, and not vice versa. The client has specified the causes that positively affect exercise. This specification also removes the possibility of a directed link from exercise to the cause. Furthermore, we know that the client has expressed the constraints that would remove the cause from consideration. In our terminology, a cause increases probability of exercise and a constraint reduces probability of exercise through removing the positive effect of a cause. Anecdotal data suggest that clients can express causes and constraints with ease. Since the client has specified which constraints work on which cause, this information too can be used to construct the links in the network.

Finally, for simplification we assume that only main effects of causes are of importance to us and interactions among causes can be ignored, except for interaction between a constraint and a cause. The structure of Bayesian network is now relatively simple. Either the cause is directly affecting success rates or the combination of the cause and the constraint is affecting success rates. This simplification ignores positive interactions between 2 causes. As we will see shortly, to the extent that these interactions exist, it will lead to wider range of parameters estimated for the Bayesian network. The analysis of diary starts with a few housekeeping tasks. Sometimes, clients may list causes that are so rare that they never occur during the 2-week diary period. These causes are not included in the analysis. Other times, 2 causes always co-occur with each other in every data entry. These 2 causes cannot be distinguished through data analysis and a new cause that reflects the combination of the two is defined and used in the analysis. Finally, it is our experience that many clients list the benefits of exercise as its cause. This may seem reasonable to the client; but benefits cannot be the cause of exercise, as benefits follow and do not precede exercise. It is important to work with the client until a set of appropriate causes are specified. More details about how to interact with the client are included in the article by Sinkule and Alemi[18] in this issue.

We draw the causal model on the basis of the client's described causes and constraints. The probability of each node is written as a function of its immediate preceding nodes. For Figure 3, this suggests 2 functions, one for $p(S \mid X, Y, \text{and } Z)$ and another for $p(X \mid C)$. For more complicated models, for example, models where causes are interlinked, there would be additional separate functions.

The law of total probability states that the effect of several mutually exclusive causes is the weighted sum of the impact of each cause:

$$p(S|X, Y, Z, \ldots) = \sum_{I=X,Y,Z,\ldots} p(S|I)p(I)$$

where $p(I) = 1$ if cause I is present, and otherwise 0.

This is read as "probability of success is weighted by the linear sum of probability of success from various causes." For example, the effect of the 3 causes on success rates in Figure 3 is given by:

$$p(S|X, Y, \text{and} Z) = p(S|X)p(X) + p(S|Y)p(Y) + p(S|Z)p(Z)$$

The probability of X as a function of C is expressed as:

$X = 1$ if cause X is present, and 0 otherwise

$C = 1$ if constraint C is present, and 0 otherwise

$p(X \mid C) = 0$ if $C = 1$

$p(X \mid C) = p(X)$ if $C = 0$

Note that $p(X \mid C)$ is 0 when both constraint C is present or cause X is absent. The probability of success as a function of both causes and constraints is obtained by substituting terms into one equation. For Figure 3, this is calculated as:

$$p(S|X, Y, Z, \text{and} C) = p(S|X)p(X|C)p(C) + p(S|Y)p(Y) + p(S|Z)p(Z)$$

The various probabilities are estimated so that the fit between the data and causal model is maximized.

One way to estimate the conditional probability of success given the various causes is to limit the data to the cases in which the cause has occurred and is not limited by any constraints. We refer to these occasions as unconstrained causes. Then the conditional probability of success given the cause is calculated as the frequency of success among occasions of unconstrained causes. For example, to calculate $p(S \mid X)$, we first restrict the cases to all situations where unconstraint causes are present and then calculate $p(S)$ in this reduced sample space. This produces a maximum estimate for the impact of the cause on success, as it assumes all successes reported in the reduced sample space did not have an alternative cause.

$$p(s|x)^{\max} = \frac{\text{Number of successful cases with unconstrained cause } x}{\text{Number of cases with unconstrained cause } x}$$

For a minimum estimate of the impact of the cause on success rate, all successful cases with alternative causes are ignored and the frequency of success recalculated. This procedure of calculating maximum and minimum estimates for the conditional probability of success given a cause takes into account the covariation among the causes.

$$p(s|x)_{\min} = \frac{\text{Number of successful cases with unconstrained cause } x \text{ and no other cause}}{\text{Number of cases with unconstrained cause } x \text{ and no other cause}}$$

Note that this method of analysis ignores the relationship among the causes. These relationships affect the minimum and maximum probability of success given the cause. Thus, despite the fact that we do not formally include cause-cause interactions in our model, the estimates of conditional probabilities are affected by potential cause-cause interactions.

Table 1

CLIENT'S 14-DAY DIARY FOR CAUSES OF EXERCISE (1 = YES, 0 = NO)

Day	Rain	Plan to commute with bike	Plan to shower at gym	Sleep early	Exercise pattern kept
1	1	1	0	0	0
2	0	0	1	1	1
3	0	0	1	1	0
4	0	1	1	0	1
5	1	1	1	0	1
6	1	1	0	0	0
7	0	0	0	0	0
8	0	0	1	0	1
9	0	0	0	0	0
10	1	1	0	1	1
11	0	0	0	0	0
12	0	0	1	0	1
13	1	0	1	0	1
14	0	1	0	0	1

EXAMPLE

Suppose we have collected the diary data in Table 1. This client had hypothesized 3 activities may help him keep an exercise routine. First activity was if the client would commute to work by bike, and thereby exercise on route. The client planned for biking to work. The second activity was if the client would take morning showers in the gym, thereby increasing the frequency of visits to the gym. The last was to sleep early, and thus be able to wake up earlier and have more time in the morning. The diary also marks rainy days, which are expected to reduce the possibility of biking to work.

The causes in Table 1 can be mapped to the causal map in Figure 3. Assume that constraint C is a rainy day, cause X is a plan to commute to work, cause Y is a plan to take showers at the gym, and cause Z is a

Table 2

CLIENT'S ADJUSTED DIARY DATA (1 = YES, 0 = NO)

Day	Plan to commute with bike	Plan to shower at gym	Sleep early	Exercise pattern kept
1	0	0	0	0
2	0	1	1	1
3	0	1	1	0
4	1	1	0	1
5	0	1	0	1
6	0	0	0	0
7	0	0	0	0
8	0	1	0	1
9	0	0	0	0
10	0	0	1	1
11	0	0	0	0
12	0	1	0	1
13	0	1	0	1
14	1	0	0	1

plan to sleep early. Note that a rainy day is assumed to affect "biking to work." The adjusted data is shown in Table 2.

Using the adjusted client's data in Table 2, we calculated the maximum and minimum conditional probability of success for various causes. Table 3 shows the reduction of diary entries if we look at the situation when the client was ready to bike to work and it was not raining.

From Table 3, we can note that in all days in which the client was ready to bike, the client did exercise. Therefore, the maximum probability of success given the plan to commute by bike is:

$$P(S|\text{plan to commute})^{\max} = 1.0$$

The minimum probability of success is obtained by eliminating days in which alterative explanations are possible. This includes day 4, as on this day the plan to shower at the gym might have led to exercise. Therefore, the minimum probability of success is calculated solely on the basis of the data in day 14 in Table 3 and is:

$$P(S|\text{plan to commute})_{\min} = 1.0$$

Table 3

EXERCISE PATTERN ON DAYS IN WHICH CLIENT WAS READY TO BIKE (1 = YES, 0 = NO)

Day	Plan to commute with bike	Plan to shower at gym	Sleep early	Exercise pattern kept
4	1	1	0	1
14	1	0	0	1

Table 4 shows the calculation of maximum and minimum probabilities of success on days in which the client was ready to take shower at the gym. The table also shows that the client exercised on 6 of 7 days in which she was ready to take a shower at the gym:

$$P(S|\text{ready to shower at gym})^{\max} = .86$$

Some of these exercise patterns might be due to other causes. Alternative explanations of causes of exercise for days 2 and 4 are available. Eliminating these 2 days leads to a minimum probability of success given the client was ready to shower at the gym:

$$P(S|\text{ready to shower at gym})_{\min} = .80$$

Table 5 shows the maximum and minimum probability of success associated with each cause. We can use

Table 4

CLIENT'S EXERCISE ON DAYS IN WHICH THE CLIENT WAS READY TO TAKE SHOWER AT GYM (1 = YES, 0 = NO)

Day	Plan to commute with bike	Plan to shower at gym	Sleep early	Exercise pattern kept
2	0	1	1	1
3	0	1	1	0
4	1	1	0	1
5	0	1	0	1
8	0	1	0	1
12	0	1	0	1
13	0	1	0	1

Table 5

MAXIMUM AND MINIMUM PROBABILITY OF SUCCESS ASSOCIATED WITH DIFFERENT CAUSES

Probability of success given the cause	Minimum	Maximum
Plan to commute with bike	1	1
Plan to shower at gym	.80	.86
Sleep early	.50	.67

this data to predict the range of probability of success on any particular day. If cases where the range of predictions exceeds .5, are classified as a successful day, these probabilities accurately predict 92.86% of observed exercise patterns. This gives us further confidence that the data in the diary have been modeled accurately. The table can also be used to list the causes from the highest to the lowest impact, so that the client can understand what is affecting her exercise patterns.

COMMUNICATING RESULTS TO THE CLIENT

Typically, analysis of diary data is done by an external group and communicated back to the client. Most clients do not need to know how the estimates of impact of various causes were arrived at. The report to the client needs to focus on findings and not methods. The report will provide the following information:

1. Advantages of keeping a diary over intuitive judgments
2. Description of causes analyzed
3. Limitations of the analysis
   - Not all causes of success are known or were monitored
   - The impact of a cause on success rate may change over time, making analysis of current data irrelevant to future patterns
4. List of causes found to affect success rates in order of impact
   - Observed impact of constraints on causes
   - Causes excluded because of invariability
   - Causes excluded because of lack of association with success
5. Variation explained by all causes examined
6. Next steps

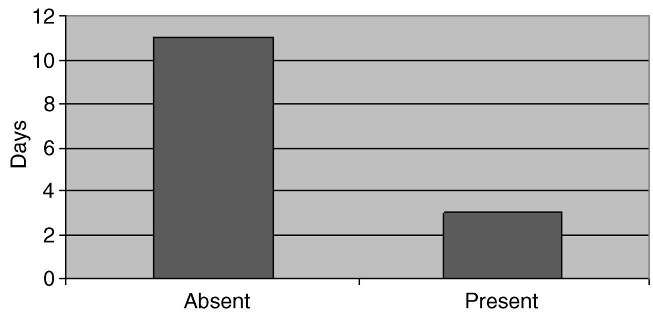

Figure 4. "Sleep early" was present in 3 days.

Feedback starts by asking clients to check their diary data. They are asked to check the frequency of occurrences of the causes and the patterns of association between 2 causes. Frequencies of occurrence of various causes are presented as a bar graph. For example, Figure 4 shows the frequency of occurrence of "sleeping early."

The association between the cause and success rate is also presented visually (the font size is altered to reflect the magnitude of the conditional probability of success given the cause) (Fig 5).

The data is presented in a face-to-face discussion with the client, allowing open question and answer periods. The presentation session is schedule ahead of time and well in advance. A paper report is provided prior to the meeting and the client is asked to anticipate the rank order of causes in predicting

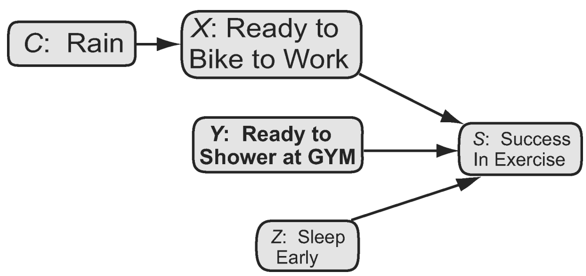

Figure 5. Causal model with font size reflecting strength of causes.

success rate prior to receiving the report. Data are presented in positive terms, emphasizing what leads to success, and not focusing on failures. No personal information appears on the written report to make sure that the client's identity is not inadvertently revealed.

At the meeting, the client is reminded of the confidentiality of the findings and that the results are for sole use by the client. A brief introduction of the team doing the analysis is made and goals of the analysis and the limitations of the diary data are highlighted. The client is told that the purpose of putting numbers on the impact of causes is to help produce insights in the exercise improvement process. The focus should be on improvement and not on measurement. The data is presented without any blame or exhortation for the client to be more committed. The client is told that the purpose is to understand how the environment affects exercise, not to put forth more effort or be more motivated. Findings are presented sequentially, and after each section there is a pause to allow clients to ask relevant questions. During the presentation, no attempt is made to defend the validity of the diary approach or methods of analysis. If the client is interested in methods of analysis, the topic is discussed in a separate session. At the end of the presentation of the findings, the client is asked to indicate how the findings will be used. Furthermore, the client is asked to generate another set of causes to monitor for the next period of diary keeping.

After the meeting, cumulative lessons learned from various periods of data collection are mailed to the client along with a revised diary to be used in subsequent periods of data collection. The summarized data from the diary sessions are used by the client in a series of self-experiments as the client gains insights about actual causes of exercise and modifies behavior on the basis of this objective information.

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Appendix

The procedure described for analysis of diary data makes a number of simplifying assumptions on the basis of the features of the task (eg, that success does not affect the occurrences of causes). The procedure, in some circumstances where causes co-occur with each other, produces wide estimates for ranges of probabilities. In this section, we provide 2 other alternative methods of analyzing diary data. The alternatives are recommended when the relatively simple method described in the main article produces too wide of an estimate.

ALTERNATIVE 1: LOGISTIC REGRESSION

The estimation of probability of success given a cause can be done using logistic regression. In logistic regression, the log of the odds of success is regressed on the remaining variables X_i, Y_i, Z_i, and so on.

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_i + \beta_2 y_i + \beta_3 z_i + \cdots + \varepsilon_i$$

In this regression equation, p_i shows the probability of success in case i. If there are n weeks of data entry, then $i = 1, 2, 3, \ldots, n$. The terms x_i, y_i, z_i, ... are the ith unconstrained diary entries for causes X, Y, Z, and so on. These variables are known and read directly from diary entries. When the cause is present, the variable is set to 1; when it is absent, it is set to 0. It is corrected in the sense that if in a particular day both the cause and the constraint are present, the indicator is changed from 1 to 0. The coefficients β_0, β_1, β_2, ... are unknown parameters and estimated from the data. The term ε_i is a residual random variable, which cannot be observed. It is assumed to have a mean of 0 and a stable variance over time. If most of data are explained by ε_i, or if the distribution of this variable is not random with a mean of 0, then causes and constraints other than those listed in the diary are affecting success rates. In addition to the logistic regression where all corrected causes are entered into the equation, separate regressions are also done for each cause by itself:

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha_0 + \alpha_1 x_i + \varepsilon_i$$

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha_0 + \alpha_2 y_i + \varepsilon_i$$

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha_0 + \alpha_3 z_i + \varepsilon_i$$

Using the coefficients estimated in logistic regression, the various conditional probabilities of success, the main effect of the cause on success, can be calculated as:

$$P(S|x_i = 1)^{\max} = \frac{e^{\alpha_0+\alpha_1}}{1+e^{\alpha_0+\alpha_1}}$$

$$P(S|x_i = 1)_{\min} = \frac{e^{\beta_0+\beta_1}}{1+e^{\beta_0+\beta_1}}$$

$$P(S|y_i = 1)^{\max} = \frac{e^{\alpha_0+\alpha_2}}{1+e^{\alpha_0+\alpha_2}}$$

$$P(S|y_i = 1)_{\min} = \frac{e^{\beta_0+\beta_2}}{1+e^{\beta_0+\beta_2}}$$

$$P(S|z_i = 1)^{\max} = \frac{e^{\alpha_0+\alpha_3}}{1+e^{\alpha_0+\alpha_3}}$$

$$P(S|z_i = 1)_{\min} = \frac{e^{\beta_0+\beta_3}}{1+e^{\beta_0+\beta_3}}$$

Table 6 shows the result of analysis using Main-Effect Logistic Regression. This table shows the result of 4 regressions, 1 with all variables included and the other 3 with each variable by itself. The minimum and maximum probabilities are estimated using above equations.

Figure 6 shows the result for the Main-Effect Logistic Regression analysis, using a causal graph. It shows that the 2 causes “Ready to bike to work” and “Ready

Table 6

MAXIMUM AND MINIMUM PROBABILITY OF SUCCESS ASSOCIATED WITH ANALYSIS USING MAIN-EFFECT LOGISTIC REGRESSION

	Independent variables				Probability of success given the cause	
Cause	**All**	**Only "plan to commute with bike"**	**Only "plan to shower at GYM"**	**Only "Sleep early"**	**Minimum**	**Maximum**
Constant	−20.63	0.00	−0.92	0.51		
Plan to commute with bike	21.47[a]	0.69			0.67	0.70
Plan to shower at gym	22.42[a]		2.71		0.86	0.86
Sleep early	−0.31			0.18	0.00	0.67

[a]Statistically significant relationship at alpha levels less than 0.05.

to shower at gym" have a statistically significant relationship with exercise.

ALTERNATIVE 2: BAYESIAN CAUSAL ANALYSIS

Often the causes of exercise co-occur. This creates difficulty in estimating the effect of each cause separately. In these circumstances, the inductive causation algorithm developed by Verma and Pearl[19] can be used to analyze the diary data and separate out the impact of each cause. This algorithm identifies a causal network from the diary data. In this network, exercise and the various causes are represented as separate nodes. A directed edge from the hypothesized cause to the exercise node designates that the diary data supports the existence of the presumed causal link. Once established, the causal network can be used to estimate the relative impact of each cause on exercise. We first discuss how the causal network can be established and later show how the influence of the cause on exercise can be estimated (Figure 7).

The Inductive Causation Algorithm has 3 steps:

1. A link is inserted between any 2 nodes that are not conditional independent of each other given any other subset of nodes.
2. For each pair of nonadjacent nodes; which have a common neighbor; arrows are directed from the nonadjacent nodes toward the shared node. This type of structure is referred to as V structure.
3. To the extent possible, the remaining nodes are directed so that no cycles or new V structures are created.

The inductive causation algorithm produces a partially directed network. If data is not sufficient to direct the arcs in the network, information supplied

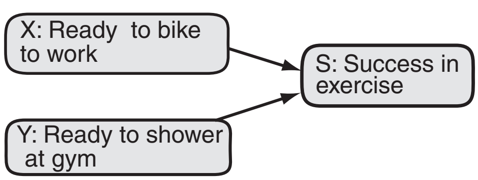

Figure 6. Result of analysis using main-effect logistic regression.

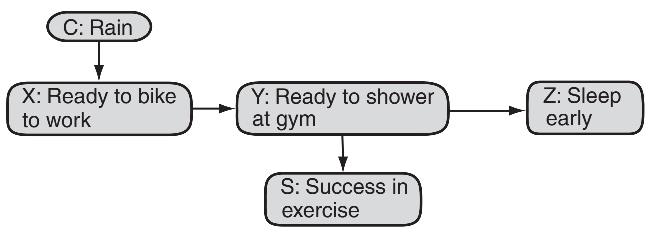

Figure 7. Analysis of Exercise Diary Using Inductive Causation Algorithm.

from the client (list of the constraints and list of the causes of exercise) can be used to orient the remaining arcs in the networks. In particular, if a link exists between a cause and the effect, it can be directed to start from the cause and end in the effect. If a link exists between a constraint and a cause, it is assumed that the link starts from the constraint and ends with the cause. Furthermore, there should not be any link back from the effect (exercise) to any of the causes as this will create a cyclical network (some clients argue that exercise reinforces causes, and therefore a cycle is necessary in the network. Because our methods work with acyclic networks, we model these situations as a cause leading to exercise and exercise leading to the same cause but at a future time).

To test the Inductive Causation Algorithm on our data, we used the publicly available and free Belief Network (BN) PowerConstructor Software. We used the relationships in Figure 3 to serve as the initial guide for discovery. We instructed the algorithm that links from exercise back to causes were forbidden. Figure 7 shows the resulting relationships recovered from data in Table 1.

The analysis of the diary supports the client's claim that planning to take showers at the gym leads to more exercise. It does not support the claim that biking to work leads to exercise as the client often cannot bike to work because of rain. Finally it does not support the claim that sleeping early will lead to exercise because of the weak association between this event and exercise.