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WHEN CAUSALITY DOES NOT IMPLY CORRELATION: MORE SPADEWORK AT THE FOUNDATIONS OF SCIENTIFIC PSYCHOLOGY[1]

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Summary.—Experimental research in psychology is typically based on an open-loop causal model which assumes that sensory input causes behavioral output. This model was tested in a tracking experiment where participants were asked to control a cursor, keeping it aligned with a target by moving a mouse to compensate for disturbances of differing difficulty. Since cursor movements (inputs) are the only observable cause of mouse movements (outputs), the open-loop model predicts that there will be a correlation between input and output that increases as tracking performance improves. In fact, the correlation between sensory input and motor output is very low regardless of the quality of tracking performance; causality, in terms of the effect of input on output, does not seem to imply correlation in this situation. This surprising result can be explained by a closed-loop model which assumes that input is causing output while output is causing input.

The variables manipulated in psychological experiments typically account for little more than 34% of the variance in behavior.[2] Researchers have assumed that this lack of predictive power is due to a large random component in the variability of behavior (e.g., Cozby, 2009). But there is reason to believe that the random component of behavioral variability cannot possibly be as large as suggested by the results of these experiments.[3] The research described in this paper tests the possibility that the poor predictive accuracy seen in psychological experiments results not

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[2]This is an estimate based on a review of 28 articles published in *Psychological Science* during the first quarter of 2008. Research articles in the January, February, and March issues of Volume 19 were reviewed. Measures of variance accounted for, in terms of η^2, were compiled for all experimental results that were statistically significant. Values of η^2 (or the equivalent r^2 value) were taken from the reports (if the values were reported) or an η^2 measure was derived from the reported t or F ratios using the reported *df*. The overall average η^2 value of .34 was based on a total of 217 reported measures of proportion of variance in the dependent variable accounted for by the independent variable.

[3]Runkel (2003) points out that even a moderate level of random variability is not at all evident in everyday behaviors such as walking and driving a car. For example, people rarely take a step and fall. But this kind of success requires enormous behavioral consistency. Even if the probability of a successful step was as high as .999, a person walking at 100 steps per minute would fall once every 10 minutes (Runkel, 2003, pp. 167). If the random component of behavior was anywhere near as large as it appears to be in conventional psychological experiments, we would see people falling all the time; in fact, we don't.

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from the random variability of behavior but, rather, from looking at behavior in terms of the wrong model.

Experimental research in psychology is based on an open-loop causal model of behavior, which is shown diagrammatically in Fig. 1. The mathematical version of this model is the general linear model (GLM), which is the basis of the main statistical methods used to analyze the data from psychological experiments (Cohen & Cohen, 1983). The open-loop model depicts behavior as the last step in a causal chain that begins with variations in an environmental variable—the independent variable in psychological experiments—and ends with variations in behavioral output—the dependent variable in experiments. Variations in the independent variable are presumed to cause concomitant variations in the sensory input to the organism—the input variable. Any relation between independent and dependent variables observed in the experiment is presumed to reveal something about the mental processes that intervene between the input and dependent variable (Levitin, 2002).

Two important assumptions are made when using the open-loop model: (1) variations in the independent variable are correlated with variations in the input variable, and (2) variations in the input variable are correlated with variations in the dependent variable (Marken, 1997, 2009). Only if these assumptions are true is it possible to infer correctly that any relation between the independent and dependent variables yields information about the nature of the causal path through the organism from input to dependent variable. In a classic paper with the provocative subtitle *Some Spadework at the Foundations of Scientific Psychology*, Powers (1978) presented evidence that these two assumptions do not hold if organisms are organized as closed-loop systems, with behavioral outputs always having feedback effects on sensory input. The evidence was obtained in a simple compensatory tracking experiment like that diagrammed in Fig. 2.[4]

The independent variable in the compensatory tracking task is the disturbance acting on cursor position; it is the variable manipulated by the experimenter. The input variable is the distance between cursor and target; it is the variable the participant senses. The dependent variable is the mouse movement that is presumably caused by variations in the input variable. The behavior in this task is clearly closed loop since the dependent variable influences the input variable that is the presumed cause of variations in the dependent variable. Powers showed that in this situation, the correlation between the independent and input variables as well

[4]Powers' analysis (1978) assumes that behavior itself, not the task being performed, is either open or closed loop. If behavior is open loop, then this is the case whether the behavior occurs in tasks that are considered closed loop (such as compensatory tracking) or open loop (such as the tasks performed in the typical psychological experiment). The same applies if behavior is closed loop.

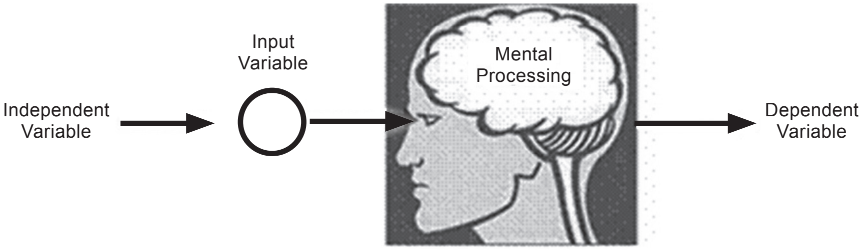

FIG. 1. The open-loop causal model of behavioral organization

as that between the input and dependent variables is close to zero even when the correlation between the independent and dependent variables is consistently greater than .99.

The low independent-input variable and input-dependent variable correlations seen in a tracking task are puzzling from the point of view of the causal model because the paths from independent to input variable and from input to dependent variable are the causal links between the independent and dependent variables. While correlation may not imply causality, causality definitely should imply correlation (Neale & Liebert, 1973; Shafer, 1996; Pearl, 2000; Anderson, 2001; Zhang & Spirtes, 2008). Yet this does not seem to be the case if behavior is closed loop.

Hypotheses

The present experiment extends Powers' research by testing the possibility that the puzzling pattern of correlations observed in compensa-

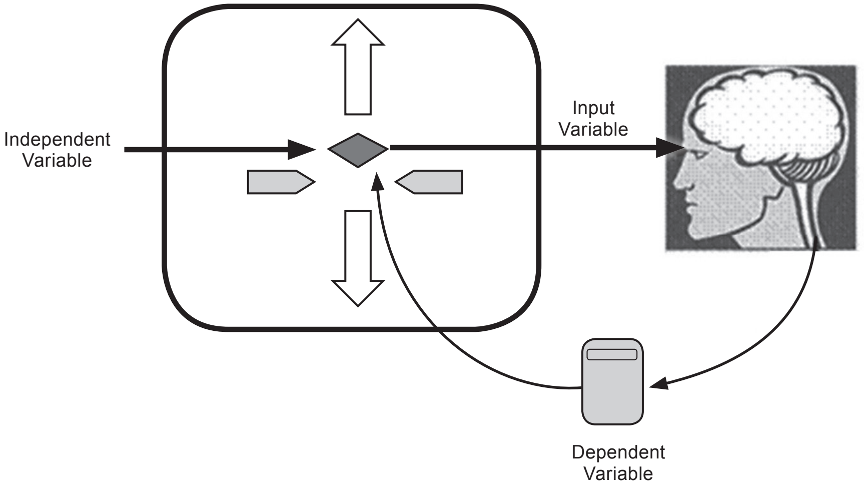

FIG. 2. Closed-loop compensatory tracking task

tory tracking depends on the difficulty of the task. The open-loop model predicts there will be a negative correlation between the cursor (input variable) and mouse movements (dependent variable) that will increase (move closer to −1.0) as task difficulty decreases. The input-dependent variable correlation should be negative because cursor variations must cause mouse movements which oppose (are negatively related to) the effects of the disturbance on the cursor. This negative input-dependent variable correlation is predicted to increase (toward −1.0) as task difficulty decreases because the causal connection from cursor to mouse movements should be strongest when cursor position changes smoothly and by easily detectable amounts, as occurs when the task is easy. The model also predicts that there will be a large, positive correlation between the disturbance (independent variable) and input variable at all levels of task difficulty given the direct physical influence of the disturbance on the cursor. The investigation reported here shows that these predictions of the open-loop model are incorrect if behavior is closed loop.

Method

Sample

Six individuals, three men and three women, participated in the experiment. Their ages ranged from 16 to 44 yr.

Apparatus

Participants performed the compensatory tracking task diagrammed in Fig. 2. The task was performed on a desktop computer on which was displayed a red diamond (the cursor) that moved vertically between two blue pointers (the fixed target). Participants were asked to vary the position of a mouse controller to keep the cursor aligned with the stationary target. The vertical position of the cursor (indicated by the white vertical arrows) was influenced by a time varying, computer-generated disturbance waveform (see Fig. 3). Cursor position was also influenced by mouse movements. To keep the cursor aligned with the target it was necessary to move the mouse appropriately to compensate for the effects of the disturbance on the cursor.

Design

The experiment used a one-way, within-subjects design. There were three levels of task difficulty: low, medium, and high. Difficulty was varied by varying the center frequency of the narrow band-filtered noise disturbance. Since the goal of the experiment was to assess the effect of task difficulty on the correlation between the disturbance (independent variable) and cursor movements (input variable) and between cursor and mouse movements (dependent variable), these correlations were the main

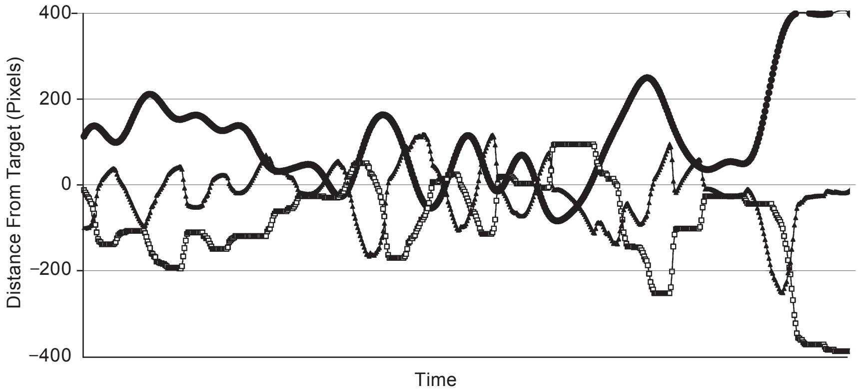

FIG. 3. Example of temporal variations in the independent variable (disturbance; —●—), dependent variable (mouse movement; —□—), and input variable (cursor; —▲—) during a one-minute tracking trial.

dependent variables in the experiment. The variables in each tracking trial were sampled at the rate of 60 Hz during each 1-min. tracking trial. Therefore, the correlations between the variables were based on 3,600 paired data points for each 1-min. tracking trial. An example of the temporal variations in the independent variable (disturbance), dependent variable (mouse movement), and input variable (cursor) observed during a tracking trial in the condition of High difficulty is shown in Fig. 3.

Each participant performed four tracking sessions at each of the three difficulty levels, a total of 12 sessions. There were six randomly generated disturbance waveforms, two for each level of difficulty. There were four 1-min. test trials at each level of difficulty; two of the four trials used one of the disturbance waveforms for that difficulty level and the other two trials used the other waveform. The order of all 12 tracking trials was randomized to counterbalance for order effects.

RESULTS

Tracking Performance

The average root mean square (RMS) tracking errors (deviations of cursor from target) on all trials in the Low, Medium, and High difficulty conditions were 6.4, 7.0, and 50 pixels, respectively. These RMS values are also measures of the average variability of the cursor (input variable) in the three conditions. The effect of difficulty on performance was significant ($F_{2,15} = 120.8$, $p < .001$; $\eta^2 = .94$). *Post hoc* pair comparisons using the Tukey HSD test showed that performance in the condition of Medium difficulty was not significantly worse (higher average RMS error) than that in the condition of Low difficulty, but performance in the condition of High difficulty was significantly worse than that in the conditions of both Medium and Low difficulty.

Independent–Input Variable and Input–Dependent Variable Correlations

The main results of the experiment are shown in Table 1. The Table shows the means and standard deviations of the correlations, over trials and subjects, between the independent and input variables and between the input and dependent variables in each difficulty condition. Contrary to the predictions of the open-loop hypothesis, the independent–input variable and input–dependent variable correlations are quite small in all difficulty conditions. The largest independent–input variable correlation was −.25 (seen in the High difficulty condition), which is not only much smaller than predicted by the open-loop hypothesis but also of the wrong sign. The largest input-dependent variable correlation (.11) occurs in the Low difficulty condition and is also much smaller than predicted by the open-loop hypothesis and also of the wrong sign.

These low correlations (see Table 1) occur in difficulty conditions where the average independent-dependent variable correlations are very large (and negative): −.9998, −.9997, and −.9638 in the conditions of Low, Medium, and High difficulty, respectively. Thus, for all difficulties there is a nearly perfect correlation between the independent and dependent variables but a very small correlation between both of these variables with the input variable, the only variable linking them.

Lagged Correlations

Since it is possible that the small input-dependent variable correlations could have resulted from failure to take into account perceptual-motor delay, these correlations were re-computed with the dependent variable lagging the input variable by from 50 to 500 msec. The changes in the correlations produced by these lags were generally quite small and always in a direction opposite that predicted by the open-loop hypothesis. The average input-dependent variable correlation went from .11 (at zero lag) to .07 (at a 500-msec. lag) in the condition of Low difficulty and from

TABLE 1

Means and Standard Deviations of the Independent–Input Variable and Input–Dependent Variable Correlations in the Low, Medium, and High Difficulty Conditions

Level of Difficulty	Independent–Input Variable Correlation		Input–Dependent Variable Correlation	
	M	*SD*	*M*	*SD*
Low	0.14	0.14	0.11	0.10
Medium	0.03	0.05	0.07	0.07
High	−0.25	0.12	−0.02	0.09

.07 (at zero lag) to .02 (at a 500-msec. lag) in the condition of Medium difficulty. In the condition of High difficulty, the average input-dependent variable correlation increased from –.02 (at zero lag) to –.39 (at a 500-msec. lag), but this result runs counter to the open-loop hypothesis, which predicts a *decrease* in the (negative) correlation between input and dependent variable with increasing task difficulty.

Simulation Exercise

Simulation of an open-loop causal model showed that, if there is a simple causal path from independent to dependent variable via the input variable, the independent-dependent variable correlation should be nearly equal to the product of the correlations between independent and input variable and input and dependent variable. The independent-dependent variable correlations based on the product of the independent-input variable and input-dependent variable correlations observed in this study are .015, .002, and .004 for the conditions of Low, Medium, and High difficulty, respectively. Virtually the same independent-dependent variable correlations are derived when using the lagged values of the independent-input variable and input-dependent variable correlations. Clearly, the independent-dependent variable correlations predicted by the open-loop causal model are not close to the observed values (–.9998, –.9997, and –.9638, in the conditions of Low, Medium, and High difficulty, respectively). Causality does not seem to imply correlation in this situation.

Repeated Disturbance

Another approach to assessing whether causality implies correlation is to look at the correlation between cursor (input variable) variations on two different tracking trials on which the same disturbance (independent variable) variations had occurred. Mouse (dependent variable) movements on different trials with the same disturbance waveform will be highly correlated because the same movements must be used to compensate for the same disturbance and keep the cursor on target. Since cursor variations are the only possible cause of mouse movements, the correlation between cursor variations on pairs of trials with the same disturbance should be high when the correlation between mouse movements on these trials is high. This prediction was tested by looking at the correlation between cursor variations on pairs of tracking trials involving the same disturbance waveform.

Table 2 shows the means and standard deviations of the correlations between mouse movements (dependent variable) and cursor movements (input variable) at each level of difficulty on pairs of trials with the same disturbance (independent variable). The surprising result is the low correlation between cursor variations (input-input variable correlations) on

TABLE 2

Means and Standard Deviations of the Input–Input Variable and Dependent–Dependent Variable Correlations in the Low, Medium, and High Difficulty Conditions

Level of Difficulty	Input–Input Variable Correlation		Dependent–Dependent Variable Correlation	
	M	*SD*	*M*	*SD*
Low	0.22	0.10	0.999	0.00
Medium	0.26	0.10	0.993	0.00
High	0.77	0.10	0.946	0.00

pairs of trials in the conditions of Low and Medium difficulty when the correlation between mouse movements (dependent-dependent variable correlations) is .9996. Participants are making almost identical movements with the mouse on pairs of trials on which cursor movements, the only possible information regarding what those movements should be, are almost completely different. The same values for the correlations between input and dependent variables on pairs of trials with repeated disturbances were found in an earlier version of this study (Marken, 1980).

The highest input-input variable correlation in Table 2 (.76) is found in the condition of High difficulty. This result is precisely the opposite of that predicted by the open-loop hypothesis. According to that hypothesis, tracking performance is best when input accurately drives output. So the best evidence for input being the cause of output should be found in the conditions of Low and Medium difficulty, in which tracking performance is best. But the only evidence that input drives output in this experiment—based on a high input-input variable correlation—is found in the condition of High difficulty in which tracking performance is actually worst. So, again, causality, in terms of the causal relation between cursor and mouse movements, which must exist, does not seem to imply correlation when behavior is closed loop.

Discussion

Closed-loop Analysis

A computer model of a closed-loop control system performing the compensatory tracking tasks used in this study showed why the causal connections from independent to input variable and from input to dependent variable do not imply correlation in this situation. A diagram of the closed-loop model is shown in Fig. 4. The model depicts variations in the input variable as simultaneously caused by variations in the independent and dependent variables. Thus, there are two simultaneous causal connections in the model; the "forward" causal connection from input to dependent variable, and the "feedback" connection from dependent to input variable.

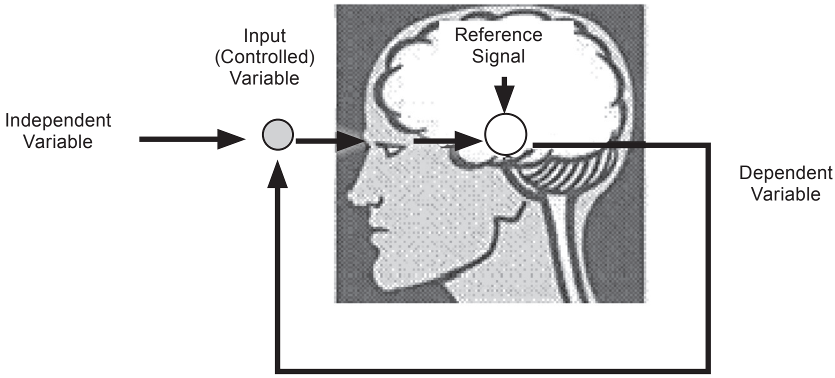

FIG. 4. Closed-loop model of tracking

The forward causal link transforms the input variable into the dependent variable via a comparison process: the input variable is compared (via subtraction) to a reference signal, which corresponds to the intended target position of the input variable. The difference between input variable and reference signal is an error signal that causes variations in the dependent variable. The parameters of the model are a temporal slowing factor (for dynamic stability) and a gain factor (which amplifies the difference between input variable and reference signal in the conversion to the dependent variable). These parameters can be adjusted to fit the behavior of the model to that of the human participants.

The closed-loop model was adjusted so that its tracking performance in each experimental condition, in terms of RMS error, was nearly the same as that of human participants. The independent-input variable correlations and the input–dependent variable correlations produced by the model in the different difficulty conditions matched those of the human participants (Fig. 4). These results show that the failure to find large independent–input variable and input–dependent variable correlations in this study does not mean that there is no causal connection between these variables. The causal connection from independent to dependent variable occurs in the closed-loop control model as the “forward” connection from independent to input variable and from input variable to comparison with the reference signal to production of the dependent variable (Fig. 4).

Because the open-loop model focuses only on the “forward” causal connection from independent to input variable and from input to dependent variable, this causal path is predicted to be reflected in the correlation between these variables. But in the control model, the two-way connection between input and dependent variable keeps this forward causal connection from showing up in the correlations between these variables.

Contribution of Neural Noise

Unlike the results for the human participants (Table 2), the input–input variable correlations produced by the closed-loop model are 1.0 at all levels of difficulty. The model can be made to match the correlations seen with humans through the addition of unfiltered random noise to the model's output. The addition of noise with amplitude less than 5% of the output range brings the input-input variable correlations for the closed-loop model down to the same range as those found for the human participants (.2 in the conditions of Low and Medium difficulty and .76 in the condition of High difficulty). Interestingly, the addition of this noise has virtually no effect on the model's tracking performance (the ability to control the input variable) due to the low-pass filtering characteristics of a closed-loop control system. RMS tracking error for the model with random noise added still matches that of the human participants in all conditions of difficulty. The level of noise added to match the input-input variable correlations for humans seems to be of the correct order of magnitude based on estimates of the magnitude of neural noise levels derived from neurophysiologic measures (Nakajima, Fukamachi, Isobe, Miyazaki, Shibazaki, & Ohye, 1978; Miller & Troyer, 2002).

Implications for Experimental Psychology

The results of the present study confirm Powers' (1978) conclusion that the independent–dependent variable relations observed in psychology experiments will not necessarily reflect the nature of the causal connections involved in behavior if the behavior under study is closed loop, that is, if the observed behavior (dependent variable) has feedback effects on the sensory cause of that behavior (input variable). This effect may be small in scientific psychology because most experiments are designed so that the behavior appears to be completely open loop. But there is reason to believe that the behavior in even the most obviously open-loop experiment may actually be closed loop (Marken, 2009). The possible closed-loop nature of the behavior in experiments can be seen by taking a closer look at the apparently open-loop behavior in a simple reaction-time experiment. One independent variable in this experiment is the onset and offset of a stimulus, such as a tone; a dependent variable is pressing or not pressing a response key. The open-loop view of the behavior in this experiment is simple: variations in the independent variable cause variations in the dependent variable. The closed-loop view, on the other hand, starts with the observation that the onset of tones does not normally cause key presses; the participant must be given instructions about what to do when the tone comes on (and goes off). The instructions for the reaction-time task tell the participant to press a key when the tone comes on but not otherwise.

According to the closed-loop view, the instructions in an experiment define an input variable that the participant is to control, a *controlled variable* (Marken, 2005). In the compensatory tracking task, instructions define the controlled variable as the distance between the cursor and target, which is to be kept at zero. In the reaction-time task, the instructions define the controlled variable as a logical relation between tone and key press, "true" when the key is pressed after the tone comes on (or not pressed when the tone is not on) and "false" when the key is pressed when the tone is not on (or not pressed when the tone is on); this controlled variable is to be kept in the state "true."

The closed-loop view of the behavior in psychology experiments can be tested using methods adapted from control engineering (Runkel, 2003, pp. 59-103; Powers, 2005, pp. 233-251). These methods involve testing to see whether a hypothesized controlled variable is actually under control. If these tests show that no variables are actually under control in an experiment, then the behavior can be considered open loop and analyses of the data based on an open-loop model, such as the GLM, are perfectly appropriate. If, however, these tests show that a variable is under control, then the behavior must be considered closed loop and a closed-loop model of the behavior is required.

Improving Prediction

The possible closed-loop nature of the behavior in psychological experiments means that the conventional approach to research may be based on an incorrect model (Marken, 2009). If this be the case, then it could explain why it has been possible to account for only a small proportion of the variance of the behavior observed in conventional experiments. The results of the present experiments show that the low effect sizes found in the typical psychology experiment could result from using an open-loop model to analyze what is actually closed-loop behavior. This would happen if the tasks carried out in such experiments are so difficult that participants cannot keep the controlled variable under control. In a reaction-time experiment, evidence of lack of control would be errors such as failure to press the key shortly after tone onset (a miss) or pressing a key before tone onset (a false alarm).

If the behavior in experiments is actually closed loop, then errors are equivalent to the deviations of the cursor from the target in a tracking task; they are a sign of loss of control. When control is poor in a tracking task—as it is when the task is made very difficult—the correlation between independent and dependent variable decreases. Were the difficulty of the tracking task used in the present study increased to the point at which RMS error was nearly three times worse than that seen in the condition of High difficulty, the correlation between independent and dependent variable would be about –.6 (instead of –.99). This independent-dependent variable correlation gives an η^2 of .36, which is close to the average η^2 of .34 found in psychology experiments based on the open-loop model. With the correct closed-loop model, however, it is possible to account for 99% of the variance of this apparently highly unpredictable dependent variable.

REFERENCES

Anderson, N. H. (2001) *Empirical direction in design and analysis*. Hillsdale, NJ: Erlbaum.

Cohen, J., & Cohen, P. (1983) *Applied multiple regression/correlation analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.

Cozby, P. C. (2009) *Methods in behavioral research*. New York: McGraw-Hill.

Levitin, D. J. (2002) Experimental design in psychological research. In D. J. Levitin (Ed.), *Foundations of cognitive psychology*. Cambridge, MA: MIT Press. Pp.115-130.

Marken, R. S. (1980) The cause of control movements in a tracking task. *Perceptual and Motor Skills*, 51, 755-758.

Marken, R. S. (1997) The dancer and the dance: methods in the study of living control systems. *Psychological Methods*, 2, 436-446.

Marken, R. S. (2002) Looking at behavior through control theory glasses, *Review of General Psychology*, 6, 260-270.

Marken, R. S. (2005) Optical trajectories and the informational basis of fly ball catching. *Journal of Experimental Psychology: Human Perception & Performance*, 31, 630-634.

Marken, R. S. (2009) You say you had a revolution: methodological foundations of closed-loop psychology. *Review of General Psychology*, 13, 137-145.

Miller, K. D., & Troyer, T. W. (2002) Neural noise can explain expansive, power-law nonlinearities in neural response functions. *The Journal of Neurophysiology*, 87, 653-659.

Nakajima, H., Fukamachi, A., Isobe, I., Miyazaki, M., Shibazaki, T., & Ohye, C. (1978) Estimation of neural noise: functional anatomy of the human thalamus. *Applied Neurophysiology*, 41, 193-201.

Neale, J. M., & Liebert, R. M. (1973) *Science and behavior: an introduction to methods of research*. Englewood Cliffs, NJ: Prentice Hall.

Pearl, J. (2000) *Causality: models, reasoning, and inference*. New York: Cambridge Univer. Press .

Powers, W. T. (1978) Quantitative analysis of purposive systems: some spadework at the foundations of scientific psychology. *Psychological Review*, 85, 417-435.

Powers, W. T. (2005) *Behavior: the control of perception.* (2nd ed.) New Canaan, CT: Benchmark.

Runkel, P. (2003) *People as living things: the psychology of perceptual control*. Hayward, CA: Living Control Systems.

Shafer, G. (1996) *The art of causal conjecture*, Cambridge, MA: MIT Press.

Zhang, J., & Spirtes, P. (2008) Detection of unfaithfulness and robust causal inference. *Minds and Machines*, 18, 239-271.

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WHEN CAUSALITY DOES NOT IMPLY CORRELATION: MORE SPADEWORK AT THE FOUNDATIONS OF SCIENTIFIC PSYCHOLOGY[1]

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Comment [dw1]: Insert Fig. 1

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independent and dependent variables yields information about the nature of the causal path through the organism from input to dependent variable. In a classic paper with the provocative subtitle “Some spadework at the foundations of scientific psychology,” Powers (1978) presented evidence that these two assumptions do not hold if organisms are organized as closed-loop systems, with behavioral outputs always having feedback effects on sensory input. The evidence was obtained in a simple compensatory tracking experiment like that diagrammed in Fig. 2.[4]

Comment [dw2]: Insert Fig. 2

The independent variable in the compensatory tracking task is the disturbance acting on cursor position; it is the variable manipulated by the experimenter. The input variable is the distance between cursor and target; it is the variable the participant senses. The dependent variable is the mouse movement that is presumably caused by variations in the input variable. The behavior in this task is clearly closed loop since the dependent variable influences the input variable that is the presumed cause of variations in the dependent variable. Powers showed that in this situation the correlation between the independent and input variables as well as that between the input and dependent variables is close to zero even when the correlation between the independent and dependent variables is consistently greater than .99.

The low independent-input variable and input-dependent variable correlations seen in a tracking task are puzzling from the point of view of the causal model because the paths from independent to input variable and from input to dependent variable are the causal links between the independent and dependent variables. While correlation may not imply causality, causality definitely should imply correlation (Neale & Liebert, 1973; Shafer, 1996; Pearl, 2000; Anderson, 2001; Zhang & Spirtes, 2008). Yet this does not seem to be the case if behavior is closed loop.

Hypotheses

The present experiment extends Powers’ research by testing the possibility that the puzzling pattern of correlations observed in compensatory tracking depends on the difficulty of the task. The open-loop model predicts there will be a negative correlation between the cursor (input variable) and mouse movements (dependent variable) that will increase (move closer to -1.0) as task difficulty decreases. The input-dependent variable correlation should be negative because cursor variations must cause mouse movements which oppose (are negatively related to)

[4] Powers’ (1978) analysis assumes that behavior itself, not the task being performed, is either open or closed-loop. If behavior is open loop, then this is the case whether the behavior occurs in tasks that are considered closed loop (such as compensatory tracking) or open loop (such as the tasks performed in the typical psychological experiment). The same applies if behavior is closed loop.

the effects of the disturbance on the cursor. This negative input-dependent variable correlation is predicted to increase (toward -1.0) as task difficulty decreases because the causal connection from cursor to mouse movements should be strongest when cursor position changes smoothly and by easily detectable amounts, as occurs when the task is easy. The model also predicts that there will be a large, positive correlation between the disturbance (independent variable) and input variable at all levels of task difficulty given the direct physical influence of the disturbance on the cursor. The investigation reported here shows that these predictions of the open-loop model are incorrect if behavior is closed loop.

METHOD

Sample

Six individuals, three males and three females, participated in the experiment. Their ages ranged from 16 to 44 yr.

Apparatus

Participants performed the compensatory tracking task diagrammed in Fig. 2. The task was performed on a desktop computer on which was displayed a red diamond (the cursor) that moved vertically between two blue pointers (the fixed target). Participants were asked to vary the position of a mouse controller to keep the cursor aligned with the stationary target. The vertical position of the cursor (indicated by the white vertical arrows) was influenced by a time varying, computer-generated disturbance waveform (see Fig. 3). Cursor position was also influenced by mouse movements. To keep the cursor aligned with the target it was necessary to move the mouse appropriately to compensate for the effects of the disturbance on the cursor.

Design

The experiment used a one-way, within-subjects design. There were three levels of task difficulty: low, medium, and high. Difficulty was varied by varying the center frequency of the narrow band-filtered noise disturbance. Since the goal of the experiment was to assess the effect of task difficulty on the correlation between the disturbance (independent variable) and cursor movements (input variable) and between cursor and mouse movements (dependent variable), these correlations were the main dependent variables in the experiment. The variables in each tracking trial were sampled at the rate of 60 Hz during each 1-min. tracking trial. Therefore, the correlations between the variables were based on 3600 paired data points for each 1-min.

tracking trial. An example of the temporal variations in the independent variable (disturbance), dependent variable (mouse movement) and input variable (cursor) observed during a tracking trial in the condition of High difficulty is shown in Fig. 3.

Comment [dw3]: Insert Fig. 3

Each participant performed four tracking sessions at each of the three difficulty levels, a total of 12 sessions. There were six randomly generated disturbance waveforms, two for each level of difficulty. There were four 1-min. test trials at each level of difficulty; two of the four trials used one of the disturbance waveforms for that difficulty level and the other two trials used the other waveform. The order of all 12 tracking trials was randomized to counterbalance for order effects.

RESULTS

Tracking Performance

The average Root Mean Square (RMS) tracking errors (deviations of cursor from target) on all trials in the Low, Medium and High difficulty conditions were 6.4, 7.0, and 50 pixels, respectively. These RMS values are also measures of the average variability of the cursor (input variable) in the three conditions. The effect of difficulty on performance was significant ($F_{2,15}$ = 120.8, $p < .001$; $\eta^2 = .94$). *Post hoc* pair comparisons using the Tukey HSD test showed that performance in the condition of Medium difficulty was not significantly worse (higher average RMS error) than that in the condition of Low difficulty but performance in the condition of High difficulty was significantly worse than that in the conditions of both Medium and Low difficulty.

Independent-Input Variable and Input-Dependent Variable Correlations

The main results of the experiment are shown in Table 1. The Table shows the mean and standard deviation of the correlations, over trials and subjects, between the independent and input variables and between the input and dependent variables in each difficulty condition. Contrary to the predictions of the open-loop hypothesis, the independent-input variable and input-dependent variable correlations are quite small in all difficulty conditions. The largest independent-input variable correlation was -.25 (seen in the High difficulty condition), which is not only much smaller than predicted by the open-loop hypothesis but also of the wrong sign. The largest input-dependent variable correlation (.11) occurs in the Low difficulty condition and is also much smaller than predicted by the open-loop hypothesis and also of the wrong sign.

Comment [dw4]: Insert Table 1

These low correlations in Table 1 occur in difficulty conditions where the average independent-dependent variable correlations are very large (and negative): –.9998, –.9997, and –.9638 in the conditions of Low, Medium, and High difficulty, respectively. Thus, for all difficulties there is a nearly perfect correlation between the independent and dependent variables but a very small correlation between both of these variables with the input variable, the only variable linking them.

Lagged Correlations

Since it is possible that the small input-dependent variable correlations could have resulted from failure to take into account perceptual-motor delay, these correlations were re-computed with the dependent variable lagging the input variable by from 50 to 500 msec. The changes in the correlations produced by these lags were generally quite small and always in a direction opposite that predicted by the open-loop hypothesis. The average input-dependent variable correlation went from .11 (at zero lag) to .07 (at a 500 msec. lag) in the condition of Low difficulty and from .07 (at zero lag) to .02 (at a 500 msec. lag) in the condition of Medium difficulty. In the condition of High difficulty the average input-dependent variable correlation increased from –.02 (at zero lag) to –.39 (at a 500 msec. lag), but this result runs counter to the open-loop hypothesis, which predicts a *decrease* in the (negative) correlation between input and dependent variable with increasing task difficulty.

Simulation Exercise

Simulation of an open-loop causal model showed that, if there is a simple causal path from independent to dependent variable via the input variable, the independent-dependent variable correlation should be nearly equal to the product of the correlations between independent and input variable and input and dependent variable. The independent-dependent variable correlations based on the product of the independent-input variable and input-dependent variable correlations observed in this study are .015, .002, and .004 for the conditions of Low, Medium, and High difficulty, respectively. Virtually the same independent-dependent variable correlations are derived when using the lagged values of the independent-input variable and input-dependent variable correlations. Clearly, the independent-dependent variable correlations predicted by the open-loop causal model are not close to the observed values (–.9998, –.9997, and –.9638, in the conditions of Low, Medium, and High difficulty, respectively). Causality does not seem to imply correlation in this situation.

Repeated Disturbance

Another approach to assessing whether causality implies correlation is to look at the correlation between cursor (input variable) variations on two different tracking trials on which the same disturbance (independent variable) variations had occurred. Mouse (dependent variable) movements on different trials with the same disturbance waveform will be highly correlated because the same movements must be used to compensate for the same disturbance and keep the cursor on target. Since cursor variations are the only possible cause of mouse movements, the correlation between cursor variations on pairs of trials with the same disturbance should be high when the correlation between mouse movements on these trials is high. This prediction was tested by looking at the correlation between cursor variations on pairs of tracking trials involving the same disturbance waveform.

Table 2 shows the mean and standard deviation of the correlations between mouse movements (dependent variable) and cursor movements (input variable) at each level of difficulty on pairs of trials with the same disturbance (independent variable). The surprising result is the low correlation between cursor variations (input-input variable correlations) on pairs of trials in the conditions of Low and Medium difficulty when the correlation between mouse movements (dependent-dependent variable correlations) is .9996. Participants are making almost identical movements with the mouse on pairs of trials on which cursor movements, the only possible information regarding what those movements should be, are almost completely different. The same values for the correlations between input and dependent variables on pairs of trials with repeated disturbances were found in an earlier version of this study (Marken, 1980).

Comment [sai5]:
Table 2

The highest input-input variable correlation in Table 2 (.76) is found in the condition of High difficulty. This result is precisely the opposite of that predicted by the open-loop hypothesis. According to that hypothesis, tracking performance is best when input accurately drives output. So the best evidence for input being the cause of output should be found in the conditions of Low and Medium difficulty, in which tracking performance is best. But the only evidence that input drives output in this experiment—based on a high input-input variable correlation—is found in the condition of High difficulty in which tracking performance is actually worst. So, again, causality, in terms of the causal relation between cursor and mouse movements, which must exist, does not seem to imply correlation when behavior is closed-loop.

DISCUSSION

Closed-loop Analysis

A computer model of a closed-loop control system performing the compensatory tracking tasks used in this study showed why the causal connections from independent to input variable and from input to dependent variable do not imply correlation in this situation. A diagram of the closed-loop model is shown in Fig. 4. The model depicts variations in the input variable as simultaneously caused by variations in the independent and dependent variables. Thus, there are two simultaneous causal connections in the model; the “forward” causal connection from input to dependent variable and the “feedback” connection from dependent to input variable.

Comment [dw6]: Insert Fig. 4

The forward causal link transforms the input variable into the dependent variable via a comparison process: the input variable is compared (via subtraction) to a reference signal, which corresponds to the intended target position of the input variable. The difference between input variable and reference signal is an error signal that causes variations in the dependent variable. The parameters of the model are a temporal slowing factor (for dynamic stability) and a gain factor (which amplifies the difference between input variable and reference signal in the conversion to the dependent variable). These parameters can be adjusted to fit the behavior of the model to that of the human participants.

The closed-loop model was adjusted so that its tracking performance in each experimental condition, in terms of RMS error, was nearly the same as that of human participants. The independent-input variable correlations and the input-dependent variable correlations produced by the model in the different difficulty conditions matched those of the human participants (Fig. 4). These results show that the failure to find large independent- input variable and input-dependent variable correlations in this study does not mean that there is no causal connection between these variables. The causal connection from independent to dependent variable occurs in the closed-loop control model as the “forward” connection from independent to input variable and from input variable to comparison with the reference signal to production of the dependent variable (Figu. 4).

Because the open-loop model focuses only on the “forward” causal connection from independent to input variable and from input to dependent variable, this causal path is predicted to be reflected in the correlation between these variables. But in the control model the two-way connection between input and dependent variable keeps this forward causal connection from showing up in the correlations between these variables.

Contribution of Neural Noise

Unlike the results for the human participants (Table 2), the input-input variable correlations produced by the closed-loop model are 1.0 at all levels of difficulty. The model can be made to match the correlations seen with humans through the addition of unfiltered random noise to the model's output. The addition of noise with amplitude less than 5% of the output range brings the input-input variable correlations for the closed-loop model down to the same range as those found for the human participants (.2 in the conditions of Low and Medium difficulty and .76 in the condition of High difficulty). Interestingly, the addition of this noise has virtually no effect on the model's tracking performance (the ability to control the input variable) due to the low pass filtering characteristics of a closed-loop control system. RMS tracking error for the model with random noise added still matches that of the human participants in all conditions of difficulty. The level of noise added to match the input-input variable correlations for humans seems to be of the correct order of magnitude based on estimates of the magnitude of neural noise levels derived from neurophysiologic measures (Nakajima, Fukamachi, Isobe, Miyazaki, Shbazaki, & Ohye, 1978; Miller & Troyer, 2002).

Implications for Experimental Psychology

The results of the present study confirm Powers' (1978) conclusion that the independent - dependent variable relations observed in psychology experiments will not necessarily reflect the nature of the causal connections involved in behavior if the behavior under study is closed loop, that is, if the observed behavior (dependent variable) has feedback effects on the sensory cause of that behavior (input variable). This effect may be small in scientific psychology because most experiments are designed so that the behavior appears to be completely open loop. But there is reason to believe that the behavior in even the most obviously open-loop experiment may actually be closed loop (Marken, 2009).

The possible closed-loop nature of the behavior in experiments can be seen by taking a closer look at the apparently open-loop behavior in a simple reaction-time experiment. One independent variable in this experiment is the onset and offset of a stimulus, such as a tone; a dependent variable is pressing or not pressing a response key. The open-loop view of the behavior in this experiment is simple: variations in the independent variable cause variations in the dependent variable. The closed-loop view, on the other hand, starts with the observation that the onset of tones does not normally cause key presses; the participant must be given instructions about what to do when the tone comes on (and goes off). The instructions for the reaction-time task tell the participant to press a key when the tone comes on but not otherwise.

According to the closed-loop view, the instructions in an experiment define an input variable that the participant is to control, a *controlled variable* (Marken, 2005). In the compensatory tracking task, instructions define the controlled variable as the distance between the cursor and target, which is to be kept at zero. In the reaction-time task, the instructions define the controlled variable as a logical relation between tone and key press, “true” when the key is pressed after the tone comes on (or not pressed when the tone is not on) and “false” when the key is pressed when the tone is not on (or not pressed when the tone is on); this controlled variable is to be kept in the state “true.”

The closed-loop view of the behavior in psychology experiments can be tested using methods adapted from control engineering (Runkel, 2003, pp. 59–103; Powers, 2005, pp. 233–251). These methods involve testing to see whether a hypothesized controlled variable is actually under control. If these tests show that no variables are actually under control in an experiment then the behavior can be considered open-loop and analyses of the data based on an open-loop model, such as the GLM, are perfectly appropriate. If, however, these tests show that a variable is under control, then the behavior must be considered closed loop and a closed-loop model of the behavior is required.

Improving Prediction

The possible closed-loop nature of the behavior in psychological experiments means that the conventional approach to research may be based on an incorrect model (Marken, 2009). If this be the case, then it could explain why it has been possible to account for only a small proportion of the variance of the behavior observed in conventional experiments. The results of the present experiments show that the low effect sizes found in the typical psychology experiment could result from using an open-loop model to analyze what is actually closed-loop behavior. This would happen if the tasks carried out in such experiments are so difficult that participants cannot keep the controlled variable under control. In a reaction-time experiment, evidence of lack of control would be errors such as failure to press the key shortly after tone onset (a miss) or pressing a key before tone onset (a false alarm).

If the behavior in experiments is actually closed loop, then errors are equivalent to the deviations of the cursor from the target in a tracking task; they are a sign of loss of control. When control is poor in a tracking task—as it is when the task is made very difficult—the correlation between independent and dependent variable decreases. Were the difficulty of the tracking task used in the present study increased to the point at which RMS error was nearly three times worse than that seen in the condition of High difficulty, the correlation between independent and dependent variable would be about –.6 (instead of –.99). This independent-dependent variable correlation gives an η^2 of .36, which is close to the average η^2 of .34 found in psychology experiments based on the open-loop model. With the correct closed-loop model, however, it is possible to account for 99% of the variance of this apparently highly unpredictable dependent variable.

References

Anderson, N. H. (2001) *Empirical direction in design and analysis*. Hillsdale, NJ: Erlbaum.

Cohen, J., & Cohen, P. (1983) *Applied multiple regression/correlation analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.

Cozby, P. C. (2009) *Methods in behavioral research*. New York: McGraw-Hill.

Levitin, D. J. (2002) Experimental design in psychological research. In D. J. Levitin (Ed) *Foundations of cognitive psychology*. Cambridge, MA: MIT Press. Pp.115-130.

Marken, R. S. (1980) The cause of control movements in a tracking task. *Perceptual and Motor Skills*, 51, 755-758.

Marken, R. S. (1997) The dancer and the dance: methods in the study of living control systems, *Psychological Methods*, 2, 436-446.

Marken, R. S. (2002) Looking at behavior through control theory glasses, *Review of General Psychology*, 6, 260-270.

Marken, R. S. (2005) Optical trajectories and the informational basis of fly ball catching, *Journal of Experimental Psychology: Human Perception & Performance*, 31, 630-634.

Marken, R. S. (2009) You say you had a revolution: methodological foundations of closed-loop psychology. *Review of General Psychology*, 13, 137-145.

Miller, K. D., & Troyer, T. W. (2002) Neural noise can explain expansive, power-law nonlinearities in neural response functions. *The Journal of Neurophysiology*, 87, 653-659.

Nakajima, H., Fukamachi, A., Isobe, I., Miyazaki, M., Shibazaki, T., & Ohye, C. (1978) Estimation of neural noise: functional anatomy of the human thalamus. *Applied Neurophysiology,* 41, 193-201.

Neale, J. M., & Liebert, R. M. (1973) S*cience and behavior: an introduction to methods of research*. Englewood Cliffs, NJ: Prentice-Hall.

Pearl, J. (2000) *Causality: models, reasoning, and inference*. New York: Cambridge Univer. Press .

Powers, W. T. (1978) Quantitative analysis of purposive systems: some spadework at the foundations of scientific psychology. *Psychological Review*, 85, 417-435.

Powers, W. T. (2005) *Behavior: the control of perception.* (2nd ed.) New Canaan, CT: Benchmark.

Runkel, P. (2003) *People as living things: the psychology of perceptual control*. Hayward, CA: Living Control Systems.

Shafer, G. (1996) *The art of causal conjecture*, Cambridge, MA: MIT Press.

Zhang, J., & Spirtes, P. (2008) Detection of unfaithfulness and robust causal inference. *Minds and Machines*, 18, 239-271.

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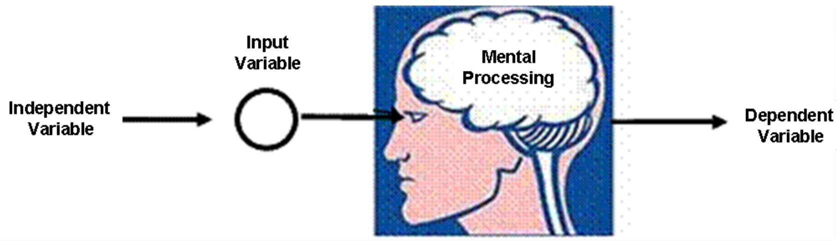

Fig. 1. The open-loop causal model of behavioral organization.

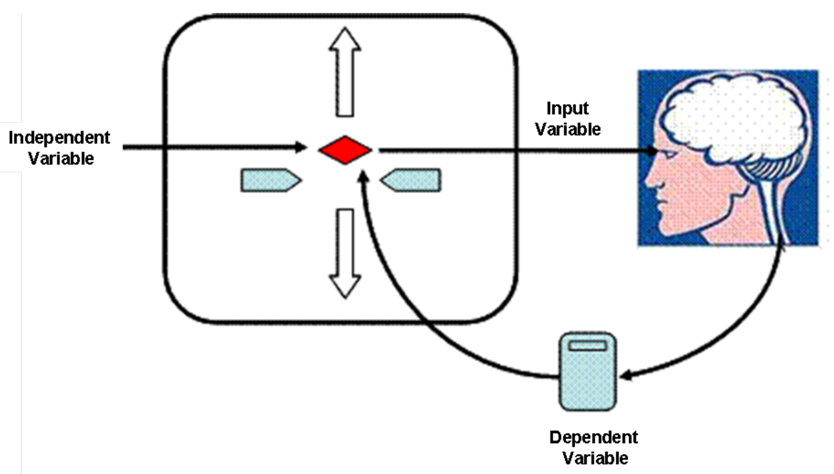

Fig. 2. Closed-loop compensatory tracking task.

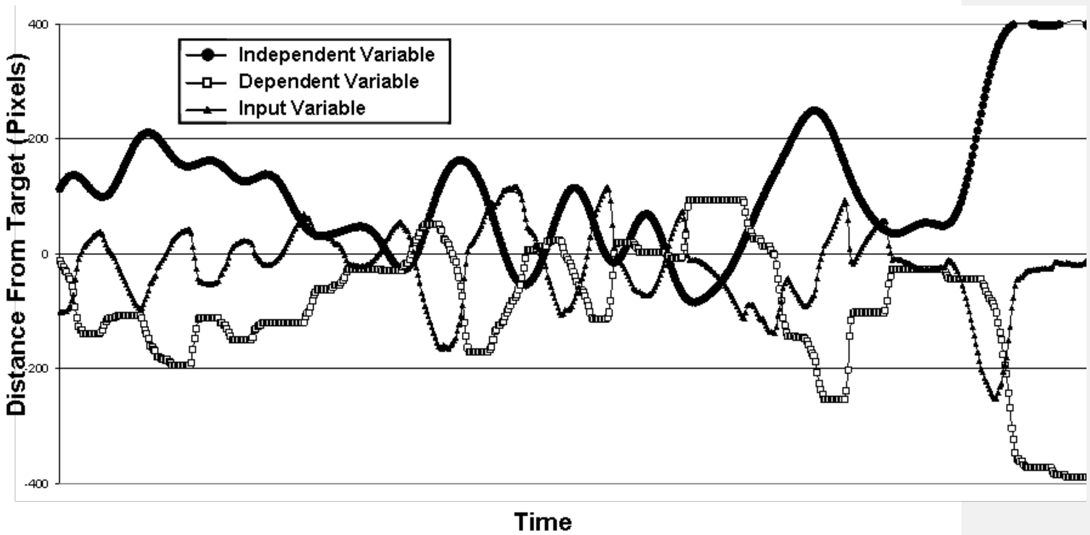

Fig. 3. Example of temporal variations in the independent variable (disturbance), dependent variable (mouse movement), and input variable (cursor) during a one-minute tracking trial.

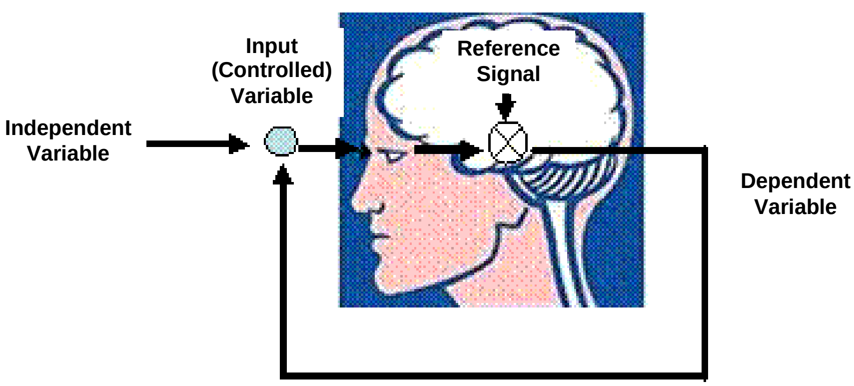

Fig. 4. Closed-loop model of tracking.

TABLE 1
Mean and standard deviation of the independent-input variable and input-dependent variable correlations in the Low, Medium, and High difficulty conditions.

Level of Difficulty	**Independent – input variable correlation**		**Input – dependent variable correlation**	
	M	*SD*	*M*	*SD*
Low	0.14	.14	.11	.10
Medium	0.03	.05	.07	.07
High	-0.25	.12	-.02	.09

TABLE 2
Mean and standard deviation of the input-input variable and dependent-dependent variable correlations in the Low, Medium, and High difficulty conditions.

Level of Difficulty	**Input – input variable correlation**		**Dependent – dependent variable correlation**	
	M	*SD*	*M*	*SD*
Low	0.22	.10	0.999	.00
Medium	0.26	.10	0.993	.00
High	0.77	.10	0.946	.00