Developing a Predictive Model of Postcompletion Errors

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Abstract

A postcompletion error is a type of procedural error that occurs after the main goal of a task has been accomplished. There is a strong theoretical foundation accounting for postcompletion errors (Altmann & Trafton, 2002; Byrne & Bovair, 1997). This theoretical foundation has been leveraged to develop a logistic regression model of postcompletion errors based on reaction time and eye movement measures (Ratwani, McCurry, & Trafton, 2008). The work presented here further develops and extends this predictive model by (1) validating the model and the general set of predictors on a new task to test the robustness of the model, and (2) determining which specific theoretical components are most important to postcompletion error prediction.

Keywords: Procedural error; postcompletion error

Introduction

Even while performing a routine procedural task that has been performed hundreds of times in the past, occasional errors still occur (i.e. a slip or lapse) (Reason, 1990). These procedural errors have been termed skill-based errors (Rasmussen & Jensen, 1974) and occur despite having the correct knowledge of how to perform a particular task. A common type of procedural error is the postcompletion error; this error is associated with forgetting a final step which occurs after the main goal of a task has been completed (Byrne & Bovair, 1997). There are several examples of postcompletion errors, such as leaving an original document on the glass of a copy machine after making a copy or failing to attach a document to an email message.

The holy grail of error research is to be able to predict when an error is going to occur before the error actually occurs (Reason, 1990). In order to be able to make advances toward error prediction, strong theoretical accounts of the cognitive mechanisms underlying procedural errors are required. In the case of postcompletion errors, these theoretical accounts do exist; Byrne and Bovair (1997) have put forward a theory specific to postcompletion errors, and Altmann and Trafton (2002) explain postcompletion errors using a general theory of goal memory, called memory for goals. Both theories are activation-based memory accounts and there is substantial overlap between the theories.

Byrne and Bovair (1997) suggest that postcompletion errors are due to goal forgetting and inattention to the postcompletion step. Specifically, postcompletion errors occur because the postcompletion step of a task is not maintained in working memory and, thus, is not executed as part of the task. The main goal of a task and the subsequent subgoals are stored in working memory and must remain active to be executed. The main goal provides activation to the subgoals. When the main goal of a task is satisfied, the goal no longer provides activation to the subgoals; consequently, the remaining subgoals may fall below threshold and may not be executed.

The memory for goals theory (Altmann & Trafton, 2002) accounts for goal-directed behavior with the constructs of activation and associative priming. The theory suggests that behavior is directed by the current most active goal and that the activation level of goals decay over time. In order for a goal to direct behavior, the goal must have enough activation to overcome interference from previous goals; thus, the goal must reach a certain threshold to actually direct behavior.

Goal activation is determined by two main constraints. The strengthening constraint suggests that the history of a goal (i.e. how frequently and recently the goal was retrieved) will impact goal activation. The priming constraint suggests that a pending goal will be retrieved and will direct behavior if the goal is primed from an associated cue. These cues can either be in the mental or environmental context.

Leveraging these theoretical accounts, Ratwani, McCurry and Trafton (2008) developed a logistic regression model predicting when a postcompletion error will occur on a computer-based procedural task. A logistic regression analysis was used because the outcome variable (occurrence of an error) was a dichotomous variable, which violates many of the assumptions of standard linear regression (Tabachnick & Fidell, 2001). A simple description of logistic regression is that it is a multiple linear regression model with a dichotomous variable as an outcome variable; a more detailed description can be found in Peng, Lee, & Ingersoll (2002).

To build their logistic regression model, Ratwani et. al. (2008) recorded and developed eye movement and reaction time measures as the behavioral indicators of the cognitive constructs outlined by the Byrne and Bovair (1997) and Altmann and Trafton (2002) theories. Specifically, three predictors were used in the logistic regression model: time between actions, total number of fixations between actions, and fixation on the postcompletion action button. The logistic regression model was as follows:

Predicted logit of Error = .12 + (time x -.001) + (total fixations x .63) + (postcompletion fixation x -5.7)

The motivation for these predictors followed directly from cognitive theory. The time predictor represents goal decay. The total number of fixations represents decay, but may also capture individual differences in decay rates and differences in visual and cognitive processing demands (Just & Carpenter, 1976; Rayner, 1998). Finally, the fixation on the postcompletion action represents inattention/attention to this action and associative priming provided by the postcompletion action button on the task interface.

Using this model, over 90% of the postcompletion error and correct actions were correctly classified on the dataset from which the model was based. The successful classification rate with this model provides some confidence that the predictors, and, more importantly, the underlying theoretical constructs which the predictors represent, are able to account for the cognitive mechanisms that contribute to postcompletion errors.

Despite the successful classification rate of this model, several important issues remain. First, the model was developed and tested on a single task. Consequently, it is difficult to determine how robust the specific model and the general set of predictors are. Second, the relative importance of each of the predictors, and the underlying cognitive constructs is unknown. For example, is decay a more important theoretical and predictive component than associative activation? How do we differentiate between the predictors?

We sought to address these issues in two ways. To determine the robustness of the logistic regression model and the set of predictors, the logistic regression model from Ratwani, et al. (2008) was applied to a new task to see how well the model could account for postcompletion errors on that task. Performance of the model was compared to a task specific logistic regression model using receiver-operating characteristic curves and by examining classification success rates. To differentiate between predictors, discriminant function analysis was utilized to linearly separate the predictors. This analysis provides insight into which specific predictors, and underlying cognitive constructs, are contributing the most in regard to predictability.

Experiment

Reaction time and eye movement data were collected on a computer-based procedural task, called the financial management task. This task has a postcompletion step and is different from the sea vessel task used by Ratwani et al. (2008). While performing the task, participants were interrupted to increase the rate of postcompletion errors (Li, Blandford, Cairns, & Young, 2008). This technique of increasing the postcompletion error rate was used by Ratwani et al. as well.

To determine the robustness of the original logistic regression model (called the sea vessel model), this model was used to predict the occurrence of a postcompletion error on the financial management task. A task specific logistic regression model (called the financial model) was also created, and the models were compared. We examined which predictors loaded significantly and the weights of the predictors. Although some differences are expected between the two models because they are based on different tasks, if the underlying theoretical constructs account for the cognitive mechanisms contributing to postcompletion errors the models should share the same general set of predictors and these models should have strong predictive power. Similarities in regression weights between the two models would suggest particularly pervasive cognitive components.

To determine the relative contribution of the predictors in the logistic regression models, discriminant function analysis was used. This statistical technique was used because logistic regression (unlike multiple regression) does not provide an indication of the importance of predictor variables (i.e. there is no indication of unique variance accounted for) (Tabachnick & Fidell, 2001). Discriminant function analysis is a linear technique that will provide an indicator of the importance of each predictor. Discriminant function analysis was used on the dataset from Ratwani et al. (2008) and on the data from this experiment to compare the relative importance of each the predictors across tasks.

Method

Particpants. Thirty-six George Mason University undergraduate students participated for course credit.

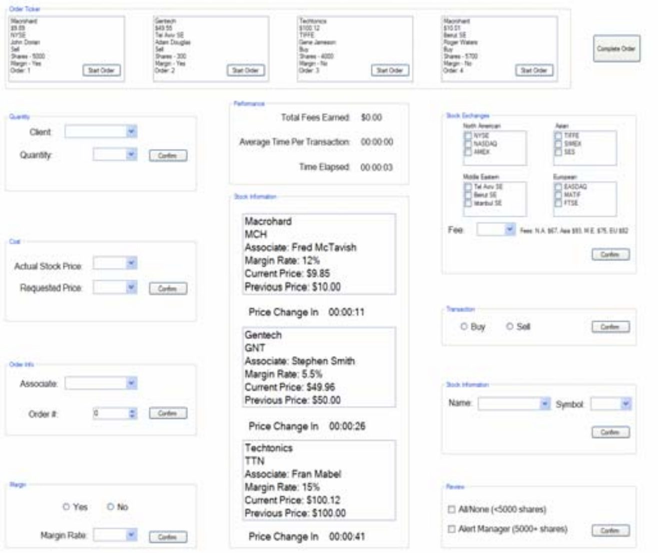
Materials. The primary task was a complex financial management task. The goal of the task was to successfully fill client's orders for different types of stocks. The orders were to either buy or sell and were presented four at a time at the top of the screen (see Figure 1). The current prices of the stocks associated with the orders were presented in the center of the screen in the Stock Information column. The actual stock price fluctuated every 45 seconds.

To complete an order, participants first had to determine which of the client orders was valid by comparing the client's requested price to the actual market price of the stock from the Stock Information column. Once an order was determined to be valid, the participant clicked the *Start Order* button for the respective stock. To actually fill the order, the participant had to enter details from the order itself and the Stock Information column in to eight different modules on the screen. Participants had to follow a specific procedure to complete the order; the specific sequence was: Quantity, Cost, Order Info, Margin, Stock Exchanges, Transaction, Stock Info, and Review. The spatial layout of the interface is quite intuitive (working down the left column and then the right column of Figure 1), unlike the sea vessel task used by Ratwani et. al (2008).

After entering information in each module the participant clicked the *Confirm* button and could then move on to the next module. After clicking confirm on the final module (the Review module), a pop-up window appeared confirming the details of the order. The participant then had to acknowledge the window by clicking *Ok*. Finally, to complete the order the participant clicked the *Complete Order* button (upper right corner). This final action was the postcompletion step and the pop-up window is a false completion signal that is generally associated with postcompletion errors (Reason, 1990).

All of the information required to complete the task is directly available on the task interface. After completing a particular module and clicking the *Confirm* button, the information disappears from the module. If a participant attempts to work on a module or clicks a button that deviates from the strict procedure, the computer emits a beep signifying that an error has been made. The participant must then continue working on the task until the correct action is completed.

The interrupting task consisted of multiple choice addition problems. Each problem contained five single digit addends and five possible solutions (4 incorrect, 1 correct). A single addition problem and solution set was presented at one time; participants completed as many problems as possible during the interruption.



Macrohard
$9.89
NYSE
John Doran
Sell
Shares - 5000
Margin - Yes
Order: 1

Gentech
$49.55
Tel Aviv SE
Adam Douglas
Sell
Shares - 300
Margin - Yes
Order: 2

Techtonics
$100.12
TIFFE
Gene Jameson
Buy
Shares - 4000
Margin - No
Order: 3

Macrohard
$10.01
Beirut SE
Roger Waters
Buy
Shares - 5700
Margin - No
Order: 4

Total Fees Earned: $0.00
Average Time Per Transaction: 00:00:00
Time Elapsed: 00:00:03

□ NYSE
□ NASDAQ
□ AMEX

□ TIFFE
□ SIMEX
□ SES

□ Tel Aviv SE
□ Beirut SE
□ Istanbul SE

□ EASDAQ
□ MATIF
□ FTSE

Fees: N.A. $67, Asia $93, M.E. $75, EU $82

Macrohard
MCH
Associate: Fred McTavish
Margin Rate: 12%
Current Price: $9.85
Previous Price: $10.00

Price Change In 00:00:11

Gentech
GNT
Associate: Stephen Smith
Margin Rate: 5.5%
Current Price: $49.96
Previous Price: $50.00

Price Change In 00:00:26

Techtonics
TTN
Associate: Fran Mabel
Margin Rate: 15%
Current Price: $100.12
Previous Price: $100.00

Price Change In 00:00:41

Order #: 0

□ All/None (<5000 shares)
□ Alert Manager (5000+ shares)

Figure 1. Screenshot of the financial management task.

Design. Control and interruption trials were manipulated in a within-participants design. The completion of one order on the financial management task constituted a trial. Participants completed twelve trials; six were control and six were interruption trials. The order of control and interruption trials was randomized. Each interruption trial contained two interruptions. There were eight possible interruption points. These points occurred after clicking the *Confirm* button following the first seven modules and after acknowledging the false completion signal, just prior to the postcompletion action. The location of the interruptions was randomized with the constraint that exactly two interruptions occurred just prior to the postcompletion step and at least one interruption occurred at each of the other seven possible locations. The interruption itself lasted for fifteen seconds.

Procedure. Participants were seated approximately 47cm from the computer monitor. After the experimenter explained the financial management and interrupting tasks to the participant, the participant completed two training trials (one with and one without interruptions). In order to begin the experiment, participants had to complete two consecutive error free trials to ensure the task was well learned.

Each participant was instructed to work at his/her own pace. When performing the interrupting task, participants were instructed to answer the addition problems as soon as the solution was known. Upon resumption of the financial management task there was no information on the primary task screen to indicate where the participant should resume. Removing this information prevented global place keeping (Gray, 2000).

Measures. Keystroke and mouse data were collected for every participant. Eye track data were collected using a Tobii 1750 operating at 60hz. A fixation was defined as a minimum of five eye samples within 10 pixels (approx 2˚ of visual angle) of each other, calculated in Euclidian distance. The *Complete Contract* button was defined as an area of interest and subtended an area greater than 1.5°. This button was separated from its nearest neighbor by at least 2°.

A postcompletion error was defined as skipping the step of clicking the *Complete Contract* button and making an action that is related to a new order on the financial management task (e.g. erroneously attempting to click the *Start Order* button or attempting to work on the first module). The percent of postcompletion errors in the interruption trials was compared to the percent of postcompletion errors in control trials. The percent of errors was a ratio of the actual number of postcompletion errors to the opportunity for a postcompletion error.

The three predictors of interest (time, number of fixations, and fixation on postcompletion step) were calculated for every postcompletion action. In the cases where there was no interruption prior to the postcompletion step, the period of measurement was from the completion of acknowledging the pop-window to the next action (i.e. correctly making the postcompletion action or making an error). In the cases where an interruption occurred just prior to the postcompletion action, the period of measurement was from the onset of the financial management task immediately following the interruption to the next action. The time predictor was measured in milliseconds. The total number of fixations predictor was a count of the number of fixations. Fixation on the postcompletion action button was a binary variable that was coded 0 if the participant did not fixate on the postcompletion button and 1 if the participant fixated on the postcompletion button.

Results and Discussion

Error Rates. Participants made a total of 27 postcompletion errors; 19 participants made at least one postcompletion error. Participants made significantly more postcompletion errors during interruption trials (*M* = 11.1%) than control trials (*M* = 1.4%), *F*(1, 25) = 18.8, *MSE* = 90.3, *p*<.001. The low error rate in the control trials shows that participants knew the task well.

Logistic Regression Models. The data from the financial management task (all postcompletion error and non-error actions, regardless of trial type) were formulated into the three predictors of interest, as described in the measures section of the method. These predictors were used to create a task specific logistic regression model (the financial model). The task specific equation was as follows:

Predicted logit of error = -2.6 + (.0003 x time) + (.11 x total fixations) – (5.5 x postcompletion fixation)

Table 1 shows the logistic regression results for this model; the beta weights are under the column labeled "β Financial." To the right of this column are the associated standard error, Walds test and degrees of freedom values. As indicated in the table, all three predictors loaded significantly in the financial model.

Table 1: Logistic regression results.

Predictor	β Sea Vessel	β Financial	SE β	Walds χ^2	df
Intercept	.12 (*n.s.*)	-2.6 (p<.001)	.4	-6.5	3
Postcompletion Fixation	-5.7 (p<.001)	-5.5 (p<.001)	1.6	-3.4	3
Total Fixations	.63 (p<.001)	.12 (p<.05)	.05	2.2	3
Time	-.001 (*n.s*)	.0003 (p<.05)	.0001	2.3	3

Table 1 also displays the beta weights from the original Sea Vessel model. Comparing the weights between the models illustrates several interesting things about the predictors. First, the postcompletion fixation predictor loaded significantly in both models and the values of the weights are nearly identical. As participants fixate on the postcompletion action button the probability of a postcompletion error decreases by nearly the same amount in each model. This comparison suggests the inattention and associative activation constructs represented by the predictor are prevalent across tasks and are important in accounting for errors.

The total number of fixations predictor is significant in both models, suggesting that this is a fairly robust predictor as well; however, the weights of the predictors are quite different. While the likelihood of a postcompletion error increases with each additional fixation in both models, the increase in probability is not as drastic for the financial task model. The difference in the value of the weights may reflect differences in the perceptual processing required in each of the tasks.

The time predictor is different in the two models; the predictor is not significant in the Sea Vessel model, but it is significant in the Financial model. In the Financial model, as time increases, the probability of making a postcompletion error increases; this behavior is in agreement with the Altmann and Trafton (2002) decay predictions.

Although there are some differences in the beta weights, there is clear overlap in two of the three predictors when examining the significance of the weights. However, simply comparing the value of the weights and the significance of the weights does not provide insight as to how well the models can actually predict when a postcompletion error will occur. Specifically, can the sea vessel logistic regression model account for the occurrence of postcompletion errors on the financial management task?

Receiver-operating characteristic analysis. To begin to examine how well each model predicts the occurrence of a postcompletion error on the data from the financial management task, a receiver-operating characteristic (ROC) analysis was conducted. For each participant on the financial management task, his or her data from each postcompletion step was entered in to each of the logistic regression models. Each model produced a predicted probability of postcompletion error. These predicted probabilities were then compared to the actual occurrence of an error to determine how accurate each model was.

Because the logistic regression models results in predicted probabilities, a threshold value must be established to categorize cases as errors and non-errors. For example, Ratwani et al. (2008) suggested a threshold value of 75% for their model on the task on which it was developed. This value means when the logistic regression model is applied to a particular postcompletion case, if the predicted probability is greater than or equal to 75%, the case should be classified as an error. If the predicted probability is under 75%, the case should be classified as a non-error.

A ROC analysis provides a method for visualizing the performance of the logistic regression models at different threshold values (Fawcett, 2006). In order to develop the ROC curves, these threshold values were systematically varied from 0 to 100 percent in each model. The predicted errors and non-errors at each threshold value were compared to the actual data to generate the true positive and false positive rates. Each of these pairs of values was then used to generate the ROC curves seen in Figure 2.

The ROC curves in Figure 2 are plotted in ROC space. Points that fall in the upper left hand corner represent perfect prediction; the points result in a high true positive rate and a low false positive rate. By visually examining Figure 2, one can see that the ROC curves for the two models are nearly identical, suggesting that the sea vessel equation is robust enough to account for the data on the financial management task.

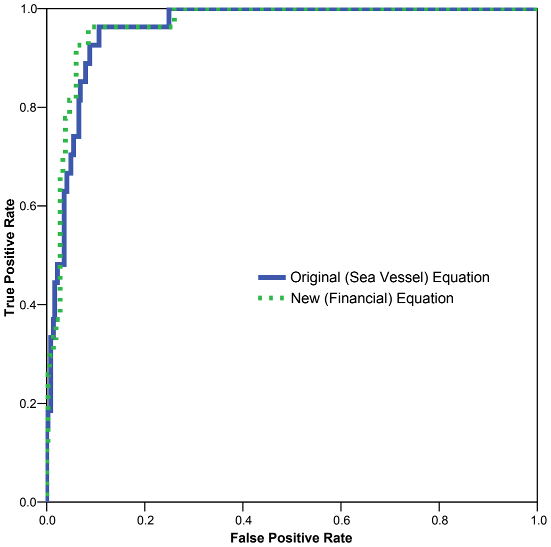


Figure 2. ROC curves for the logistic models.

In order to quantitatively determine how robust the logistic regression models are at predicting postcompletion errors on this dataset, the area under the ROC curve can be examined. The area under the curve represents the probability that the logistic regression model will rank a randomly chosen positive instance (i.e. an error) higher than a randomly chosen negative instance (i.e. non-error) (Fawcett, 2006; Macmillan & Creelman, 2005). The area under the ROC curve for the sea vessel model is .96. The area under the curve for the financial model is .97. These values are considered excellent and suggest that the logistic regression models are correctly ranking nearly every case.

To illustrate the robustness of the sea vessel model, a confusion matrix was created by applying the model to the financial dataset. A 75% threshold was used to classify non-errors and error. This threshold was determined to maximize true positives and minimize false positives for this particular logistic regression model on the sea vessel task (Ratwani & Trafton, under review). As can be seen in Table 2, the sea vessel model predicts more than 90% of the postcompletion errors. This result is based on taking the equation “out of the box”; improved performance can be achieved by determining the optimal threshold on the financial management task.

A confusion matrix was also generated using the financial logistic regression model. This model was applied to the financial management dataset using a threshold value of 30%. Based on the ROC analysis, this threshold value maximizes true positives and minimizes false positives. Table 3 shows the results. Comparing the tables, it is obvious that both models are very accurate. The financial model has a 4% higher true positive rate.

The ROC analysis and the confusion matrix provide strong evidence for the robustness of the sea vessel model and for the set of predictors in the model. The sea vessel predicted over 90% of the errors on the new financial task with the 75% threshold, suggesting that the underlying theoretical constructs are accounting for the cognitive mechanisms contributing to postcompletion errors, regardless of task.

From an applied aspect, note that both models accurately identify over 90% of actual errors and have results in less than 10% false positives, despite the differences in threshold values. The robustness and accuracy of the model strongly suggests that these models could be used in an applied context to prevent errors before they occur. The fact that the model does not make many false alarms in either direction suggests that any system that relies on this information would be usable as well as accurate.

Table 2. Confusion matrix based on the sea vessel model.

	Actual Value	
Predicted Value	True Positive 25 (92.6%)	False Positive 37 (10%)
	False Negative 2 (7.4%)	True Negative 328 (90%)

Table 3. Confusion matrix based on financial model.

	Actual Value	
Predicted Value	True Positive 26 (96.3%)	False Positive 34 (9.3%)
	False Negative 1 (3.7%)	True Negative 328 (90.7%)

Discriminant function analysis. Logistic regression is an excellent statistical technique for maximizing predictive value, but it is difficult to draw conclusions about the relationships between predictors and the outcome variable. Specifically, our interest was in determining which predictor has the strongest relationship to the occurrence of an error and to examine whether these relationships hold true across models and tasks. To answer these questions, discriminant function analysis (DFA) was used. DFA is a linear analysis technique to predict group membership from a set of predictors. Critically, DFA provides information on the strength of the relationship between each predictor and the outcome variable and the importance of these predictors. It is this aspect of DFA that we are most interested in.

Ratwani et al. (2008) did not perform a discriminant function analysis (DFA) on the sea vessel dataset. Therefore, we have taken that dataset, as well as the data from the financial management task, and conducted a DFA on each set of data. As expected, there was a strong association between the set of predictors and the occurrence of an error in Ratwani et al.’s (2008) dataset, χ^2 (3) = 350.9, p<.001. There was also a strong association between the set of predictors and the occurrence of an error, χ^2 (3) = 126.9, p<.001, in the financial management dataset. These findings confirm the findings from logistic regression analyses.

To determine the relationship of each predictor to the classification function, we examined the canonical coefficients for each model. These coefficients indicate the unique contribution of each predictor to the classification function (outcome variables). This value is analogous to determining the unique variance accounted for by each predictor in multiple regression. Table 4 shows the canonical coefficients for each of the models on their respective datasets. Whether the coefficient is positive or negative is irrelevant for determining the strength of association to the classification function.

Table 4. Canonical coefficients for each model.

	Standardized Canonical Discriminant Function Coefficients	
Predictor	Sea Vessel Model	Financial Model
Postcompletion Fixation	.88	.73
Total Fixations	-.74	.-27
Time	.35	-.43

In both models, the postcompletion fixation predictor has the strongest relationship to the classification function. This finding suggests that cue association and inattention to the postcompletion action are the most important theoretical components accounting for postcompletion errors.

In the sea vessel model, the total fixations predictor has a stronger relationship to the classification function than time. However, in the financial model, time has a stronger relationship to the classification function than total fixations. It is also interesting to note that there is a bigger difference in the total fixations predictor between the two models as compared to the time predictor. While both of these predictors represent decay, total fixations may also represent differences in visual processing and this may account for the differences observed here. The weights from the logistic regression models and the discriminant function coefficients suggest that the total number of fixations predictor and the time predictor are more variable across tasks than the postcompletion fixation predictor.

General Discussion

The logistic regression and DFA analyses suggest that the postcompletion action fixation was the most important predictor. Most striking was the nearly similar beta weight for the postcompletion fixation in both models. While one might argue that a fixation on a to be completed action button is generally necessary before the physical clicking of the button in computer-based tasks, there were several instances where participants fixated on the postcompletion action button and failed to complete the step. Additionally, this measure is not the only measure nor is it the only measure for other error types (Ratwani & Trafton, under reivew). We argue that these analyses provide strong evidence that inattention and cue association are critical theoretical components accounting for postcompletion errors, regardless of the task.

The time and total number of fixations predictors are also important components of the logistic regression model. However, several questions remain about the differences in the weights of the predictors and the differences in the DFA correlations between the predictors and the classification function. Total number of fixations may be accounting for individual differences in visual processing and possibly individual differences in decay rates. The variability in the total number of fixations predictor may be due to the different visual processing demands of the two tasks. It is unclear why time, a clear measure of goal decay, was not a consistent predictor in both logistic models. It is clear that neither the Byrne and Bovair (1997) nor the Altmann and Trafton (2002) can adequately account for these subtleties in their current form. The relationship between these two predictors needs to be examined further.

Regardless of these differences, these results show the robustness of the predictive power of the original logistic regression model and the general set of predictors. This model accounted for over 90% of the postcompletion errors on a new task. The overall predictive power of this logistic regression model on two different tasks is encouraging and suggests that an understanding of the cognitive mechanisms underlying procedural errors can lead to prediction.

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