Organizational Behavior and Human Decision Processes xxx (2011) xxx–xxx

Contents lists available at ScienceDirect

Organizational Behavior and Human Decision Processes

journal homepage: www.elsevier.com/locate/obhdp

A detection model of college withdrawal

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ARTICLE INFO

Article history:
Received 17 August 2009
Accepted 14 December 2010
Available online xxxx
Accepted by Paul Levy

Keywords:
College withdrawal
Signal detection theory
Shocks
Turnover
Quit

ABSTRACT

Many students during their college careers consider withdrawing from their respective college or university. Understanding why some students decide to withdraw yet others persist has implications for both the well being of students as well as for institutes of higher education. The present study develops a model of the decision to withdraw drawing on theories of voluntary employee turnover from organizational psychology and signal detection theory from the cognitive sciences. The model posits that precipitating events or shocks (e.g., changes in tuition) lead students to consider withdrawing from the university. If the evidence surpasses a criterion then the student decides to withdraw. The model was used to identify shocks students were sensitive to and to test hypotheses about the underlying decision process. The theoretical implications of this model in terms of understanding and predicting student withdrawal decisions and voluntary employee turnover decisions are discussed.

A detection model of college withdrawal

An unavoidable fact in higher education is that some students persist in obtaining a degree, while others withdraw. The National Center for Education Statistics reported that only 57% of bachelor's or equivalent degree-seekers that began college in 2001 had within 6 years graduated from that same college. This overall completion rate is qualified by a number of dimensions. Females have a greater completion rate than males (60% vs. 54%). Completion rates also differ by race and ethnicity, with Asian/Pacific Islanders having the highest rate and American Indian/Alaskan natives the lowest (66% and 40%, respectively; Knapp, Kelly-Reid, & Ginder, 2009). Understanding why some students persist at their chosen institution and others decide to withdraw has important implications for a range of institutional processes including student admissions, intervention efforts for at-risk students, directions for federal funding, and maintenance of a rigorous athletic program (Hagedorn, 2005).

Most descriptive level explanations of student retention are structural in nature. They focus on how academic, social–psychological, and environmental factors, predict intermediate attitudes such as different levels of satisfaction and perceptions of poor fit with the university setting, which in turn predict college turnover (Aitken, 1982; Bean, 1985; Braxton & Lee, 2005; Tinto, 1975). Similar approaches focus on the role and availability of different support systems and their impact on student persistence (Nora, 2004; Nora & Cabrera, 1996). An alternative approach, one we take, is to focus on the process students use to decide to withdraw from college. To do so, we developed a formal cognitive model of the decision process to withdraw from college.

Formal cognitive models

Before going further we should clarify what a formal cognitive model is and why it is important in theory development. A formal cognitive model uses mathematical or computer language to specify how basic cognitive processes give rise to a phenomenon of interest (Busemeyer & Diederich, 2010). In the case of this paper, we are interested in modeling how students decide to withdraw from university. To be certain, computational models have been used to address similar questions relevant to industrial/organizational behavior, but the focus of these models have tended to be at the level of understanding the interaction of people in the complex systems of organizations (Ilgen & Hulin, 2000). Formal cognitive models provide a different level of analysis then these computational models.

Formal cognitive models also differ in important ways from other models often used in psychology. By formally specifying a theory in mathematical language the model can synthesize the process and/or system in an observable and testable form. In other words, one can use the model to see how the process works (or does not work) to produce the behavior of interest (e.g., a decision). One can also then add or subtract features to the model (e.g., variability) or change parameter values within the model and then

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doi:10.1016/j.obhdp.2010.12.001

Please cite this article in press as: Pleskac, T. J., et al. A detection model of college withdrawal. *Organizational Behavior and Human Decision Processes* (2011), doi:10.1016/j.obhdp.2010.12.001

make precise predictions how the behavior of interest should change. Another implication of fully specifying a process is that one can directly test how well a particular process accounts for the phenomenon of interest. In comparison, conceptual models that rely on natural language and/or box-and-arrow diagrams to describe a process typically must be tested indirectly using off-the-shelf scales and questionnaires measuring constructs/processes (see Hintzman, 1991; Neufeld, 2007). Moreover, by synthesizing theory in a formal language cognitive models often provide a new perspective on complex constructs or processes of interest. For example, in the clinical sciences formal models have revealed the relationships between: (a) reward processing and risky drug use (Pleskac, 2008); (b) social information processing and sexually coercive behavior (Treat, McFall, Viken, & Kruschke, 2001); and memory storage/retrieval process and schizophrenia and alcoholism (Riefer, Knapp, Batchelder, Bamber, & Manifold, 2002). In this paper, we hope to use formal models to provide new insight onto college withdrawal decisions.

Formal cognitive models are also distinct from statistical models. Statistical models such as linear regression, structural equation models, or psychometric functions, aim to characterize aspects of a phenomenon of interest, but do not precisely specify how a process or set of processes gave rise to the phenomenon (Luce, 1995). Formal cognitive models, in comparison, are grounded in the basic principles of cognition and aim to open the black box specifying how internal information processing mechanisms give rise to the observed phenomenon. An advantage of this approach is that the parameters in a formal cognitive model are grounded theoretically in the particular process the model describes. Thus, the parameters provide independent, theoretically motivated means to measure how different factors impact the cognitive process and ultimately shape the behavior of interest. In this paper, for example, we will use a formal model of college withdrawal decisions to measure the impact of precipitating events or *shocks* on students' decisions to quit and the parameter precisely identifies where in the process the shock impacts the decision.

There are a number of ways to develop formal cognitive models (Busemeyer & Diederich, 2010). Two common methods are to: (a) formalize an established conceptual model of a process and (b) to adapt a formal mathematical model to account for the phenomenon of interest. In this paper, we use both of these methods. The model draws on principles from the unfolding model, a conceptual model of voluntary employee turnover (Harman, Lee, Mitchell, Felps, & Owens, 2007; Holtom, Mitchell, Lee, & Inderrieden, 2005; Lee & Mitchell, 1994; Lee, Mitchell, Wise, & Fireman, 1996). We also employ signal detection theory, a formal modeling framework used in the cognitive sciences to explain the decision process (Green & Swets, 1966; Tanner & Swets, 1954).

An advantage of the specific approach we took in developing our model is that we can uncover processing assumptions that were previously unnoticed or untested in the literature. In the case of turnover decisions, different processing assumptions *can be* and *have been* made regarding just how the decision is made. For instance, the basic premise in the unfolding model of voluntary turnover is that employees (or students in our case) follow different discrete processing paths in deciding to quit (Harman et al., 2007; Holtom et al., 2005; Lee & Mitchell, 1994; Lee et al., 1996). From a signal detection perspective, these discrete paths are discrete states where you are either deliberating or not or you are enacting a script or not. Many successful models of decisions in the cognitive sciences, however, do not assume discrete states underlie a decision, but that a decision is made by comparing an internal continuous level of evidence to a criterion level of evidence. In this case, one quits only if one's internal level of evidence exceeds this criterion. These different processing hypotheses give rise to different testable formal decision models. Fitting the different models directly to data and comparing them via goodness-of-fit measures can, in turn, directly test these hypotheses. Distinguishing between these different processing hypotheses is important for a better basic understanding of college withdrawal decisions. Moreover, as we illustrate in the discussion, a better micro-level understanding of the properties of turnover decisions may aid our understanding of macro-level phenomena like the changes in withdrawal rates across academic years.

Voluntary employee turnover

The decision to withdraw from a university is in many ways analogous to an employee's decision to quit a job (for a similar argument see Bean, 1980, 1983). Both involve a decision – often made at the individual level – to leave a larger organization and in many cases involve individuals considering a transfer to another institution. Both decisions also directly affect the culture of an organization and its ability to survive (cf. Simon, 1947). The two decisions, however, are not perfect analogs. For example, students are also consumers of a product. Thus, a student withdrawing from a university may in fact be more consistent with a customer leaving a product for a new brand or company. Some have suggested these two seemingly dissimilar decisions – employees quitting and customers leaving a brand or company – may follow the same general underlying process of deciding to quit (March & Simon, 1958, p. 127). Thus, it seems reasonable to assume that in developing a formal cognitive model of the decision to withdraw from school we can generalize from what is known about how employees decide to quit.

Focusing on an employee deciding to quit, March and Simon (1958) conceptualized this process in terms of the utility individuals place on staying with or leaving their organization. They suggested utility was both a function of the desire to stay and also the perceived ease of movement from the organization. Operationalizing desirability in terms of employee satisfaction and ease of movement in terms of the number of job alternatives, this framework has been successful in identifying several moderators of turnover decisions (Hom, Caranikaswalker, Prussia, & Griffeth, 1992; March & Simon, 1958; Mobley, 1977; Porter & Steers, 1973).

A critical aspect missing from March and Simon's (1958) turnover framework is that in some cases external events may prompt employees to decide to quit independent of the desirability of leaving and the ease of leaving. Lee, Mitchell and colleagues contend that for many turnover decisions, precipitating events or *shocks* lead individuals to consider quitting (Harman et al., 2007; Holtom et al., 2005; Lee & Mitchell, 1994; Lee et al., 1996). The unfolding model describes how shocks enter the decision process to quit (Holtom et al., 2005; Lee & Mitchell, 1994; Lee et al., 1996). The basic idea of the unfolding model is that there is not one clear-cut path that leads to a decision to quit an organization. Instead different paths lead to an employee quitting a job or in our case to a student withdrawing from the university (see Table 1). Some paths occur after a student experiences a shock. Path 1 depicts a course where the decision to withdraw is certain to occur after the student detects a shock. In the case of Path 1, a shock triggers a pre-existing script that directs the person to leave with little deliberation. Paths 2 and 3, in comparison, do not have a pre-existing rule or script. Instead, in response to a shock an individual compares his or her present surroundings with personal standards defined by values, expectations, and/or goals. This comparison process can put an employee into either a state of fit or misfit. When employees are in a state of misfit then they are more likely to withdraw. Finally, according to the unfolding model, some withdrawal decisions happen in the absence of a shock and are the result of a build-up of dissatisfaction (Paths 4a and Paths 4b).

The unfolding model is broad and describes a large proportion of the different possible types of voluntary employee decisions to

Table 1
Illustration of Lee and Mitchell's (1994) unfolding model.

	Initiating event	Cognitive/emotional process	Search behavior	Quit decision
Path 1	Shock	Prompts quitting script enactment	None	Automatic
Path 2	Shock	Prompts comparison of current situation to individual's values, expectations, and goals	None	Fairly automatic
Path 3	Shock	Prompts comparison of current situation to individual's values, expectations, and goals	Search for alternatives	Deliberate
Path 4a	No shock	Accumulating dissatisfaction	None	Fairly automatic
Path 4b	No shock	Accumulating dissatisfaction	Search for alternatives	Deliberate

Adapted from Harman et al. (2007) Table 1.

quit (Holtom et al., 2005; Lee, Mitchell, Holtom, McDaniel, & Hill, 1999; Lee et al., 1996). Nevertheless, the model has some limitations. One is that it is quite complex. While this complexity clearly aids the unfolding model's ability to account for a wide range of decisions it also comes at a cost. In particular, model complexity can obscure one's ability to assess whether the model corresponds to the actual underlying decision process (for a discussion on model complexity see Myung, 2000). In other words, model complexity can lead to over fitting. In the case of the unfolding model this appears to be a genuine concern. For example, the data used in the present study – students' rated intention of withdrawing – had at most eight degrees of freedom. Based on our understanding of the unfolding model, it would be difficult to formally specify the entire unfolding model with fewer than eight free parameters. Thus, the model would be saturated in terms of accounting for the eight degrees of freedom within the data and as a result, without constraining the model in theoretically meaningful ways, one cannot assess how well the model accounts for the data. The detection models we develop next are simpler and have fewer free parameters making it possible to directly test how well a particular model corresponds to the data on hand. This ability allows us to test a number of hypotheses about the underlying process of college withdrawal decisions.

A family of detection models of college withdrawal

A detection model provides a different means to model college withdrawal decisions than the unfolding model and is based on signal detection theory (Green & Swets, 1966; Tanner & Swets, 1954). Signal detection theory actually provides a framework of possible models. The basic process proposed in any of our detection models of college withdrawal is that each day a student experiences a world full of everyday events (e.g., they go to class, eat in the cafeteria, exercise at the gym, study, meet up with friends, go out on dates, etc.). Sometimes though a shock is embedded within the everyday events. Both the everyday events and the shocks contribute to an internal state of evidence x concerning whether a student should leave or not. In other words, according to our models, the shock is analogous to a signal – a signal to withdraw – and the everyday events are analogous to background noise. The shocks themselves or other external events (e.g., having to sign up for classes next semester, or a parent/friend/teacher asking the student if they intend to persist at school) prompt the student to take a sample of evidence x and use this evidence to decide if they want to withdraw or not. Thus, we can divide the world into four different outcomes for college withdrawal decisions (see Table 2). Some decisions to withdraw occur following a shock (Outcome I). Other decisions to withdraw occur when a student does not experience a shock (Outcome III). In comparison, a decision to stay might also occur following a shock (Outcome II) or not (Outcome IV).[1]

[1] We have dropped the typical language of hits and false alarms commonly used in signal detection theory because in withdrawal and turnover decisions there is no correct or incorrect answer.

Table 2
The different outcomes possible for college withdrawal decisions.

	Decision	
	Withdraw	Stay
External event		
Shock	Outcome I	Outcome II
No shock	Outcome III	Outcome IV

Gaussian detection model of college withdrawal

From this basic set of processes, we can derive a number of possible formal cognitive models of the decision process used to withdraw. One such model is a Gaussian detection model. A Gaussian model has been successful in accounting for a number of decision processes ranging from those used in recognition memory (Ratcliff, Gronlund, & Sheu, 1992) to other higher-order decisions (Wallsten, Bender, & Li, 1999). It has also been used in other applied settings including lie detection (Ben-Shakhar, Lieblich, & Bar-Hillel, 1982), clinical assessment (McFall & Treat, 1999), and stress assessment in cardiac patients (Young, Ignaszewski, Fofonoff, & Kaan, 2007). In the Gaussian detection model, everyday events produce a distribution of evidence x that is normally distributed with a mean of 0 and with a standard deviation s_{everyday}. Likewise, after a shock the distribution of evidence x is normally distributed with a mean of d' and a standard deviation of s_{shock}. Thus, shocking events as well as everyday events give rise to variable levels of evidence. A Gaussian signal detection model is illustrated in Panel A of Fig. 1.

To make a decision, students compare their internal level of evidence with a response criterion k (solid black line in Panel A of Fig. 1). This criterion represents the magnitude of evidence that must be observed in order to justify leaving. That is, if the internal level of evidence x is greater than the criterion k, then the student withdraws from the university. Thus, the response criterion k indexes different biases that students have due to, for example, the costs and benefits associated with withdrawing or persisting. As k gets smaller (k moves to the dotted lines marked a and b in Panel A of Fig. 1) the more biased a student becomes to withdraw, regardless of the precipitating events. If we specify the values of d', s_{normal}, s_{shock}, and a value for k (e.g., at the bolded criterion labeled as c in Fig. 1), we can use the model to calculate the predicted probabilities of the different outcomes in Table 2. To account for rating data, where a student rates on a scale from 1 to 5 their intent to withdraw (the response mode of our study), the Gaussian model uses four response criteria as shown in Fig. 1. According to the model, students select a rating according to their appraisal of the evidence and its location relative to the response criteria.

On closer inspection, some properties of the unfolding model might actually be consistent with the Gaussian detection model. Image theory (Beach & Mitchell, 1998) – the theoretical foundation of the unfolding model – posits that when an individual compares his or her present surroundings with personal standards defined by values, expectations, and/or goals they conduct what is called a

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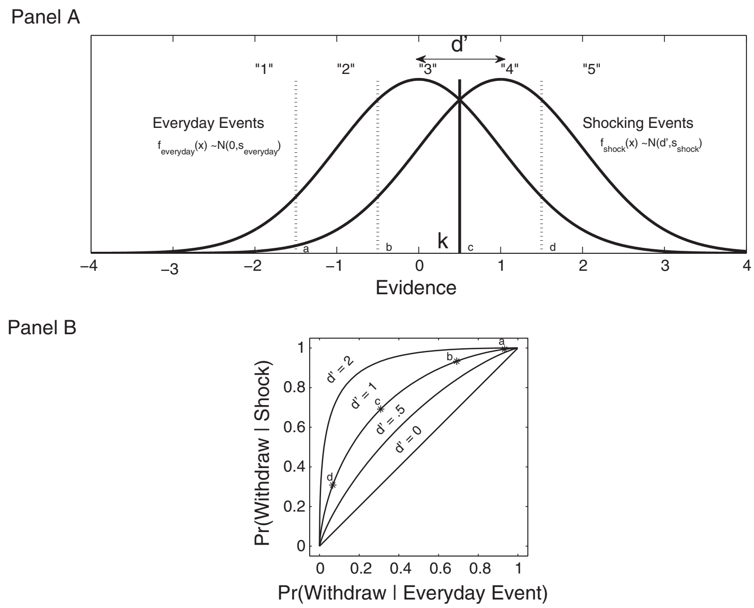

Fig. 1. The Gaussian equal variance model of college withdrawal decisions. Panel A illustrates the model and its associated parameters. The model assumes that at the time of a decision an individual forms an internal level of evidence. The evidence has two different distributions depending if the student has experienced a shocking event ($N(d', s_{\text{shock}})$) or an everyday event ($N(0, s_{\text{everyday}})$). If the internal evidenceis greater than a criterion k then the student withdraws otherwise they stay. The model separates between the sensitivity of an individual to a shocking event indexed by d' and the contextual factors present at the time of the decision indexed by the criterion k. Panel B illustrates four different Receiver Operator Characteristic (ROC) functions each with a different level of sensitivity. To account for rating data, where a student rates on a scale from 1 to 5 their intent to withdraw (the response mode of our study), the Gaussian model uses four response criteria as shown in Panel A and assumes a student maps a rating (1, 2, 3, 4 or 5) in accord to the level of evidence they sample relative to those criteria.

compatibility test. These personal standards are called images and the compatibility test examines if the environment is consistent with these images or if there are violations. According to image theory (Beach & Mitchell, 1998), "Each violation is all-or-none. The decision rule is whether the weighted sum of the violations exceeds some absolute rejection threshold" (p. 15). Within the unfolding model, this compatibility test is used in Paths 2 and 3 to determine if leaving is an appropriate option (Table 1).Based on this process, it follows that if the decision to leave is based on a weighted sum of the violations as the compatibility test suggests, then according to the central limit theorem as the number of violations increases the distribution of the sum of the violations will be approximately normally distributed. In sum, a Gaussian detection model – a model that assumes a continuous level of internal evidence – may best describe the decision process for many turnover decisions. This process level prediction forms the basis of our first hypothesis about the underlying decision process:

> *Gaussian hypothesis: If the decision to withdraw follows the process described in the Gaussian detection model where a continuous level of evidence to withdraw is generated and compared to a criterion to decide to quite, then this should result in the students' intent to withdraw data being best fit by the Gaussian detection model.*

Threshold model of college withdrawal

Recall the unfolding model posits that students adopt one of several qualitatively different paths in deciding to withdraw (Table 1). These different discrete paths generate a second alternative hypothesis for the decision process: discrete internal evidence states. In comparison, as we just discussed, in the Gaussian model the decision is made based on a continuous latent level of evidence, where the magnitude of the evidence reflects how strongly the students' internally sampled data supports withdrawing (e.g., number of violations between current environment and personal standards as in image theory's compatibility test). Thus, different underlying information processing assumptions *can be* and *have been* made about how people decide to quit. One goal of this modeling venture is to test which processing assumption – discrete or continuous evidence states – best accounts for the data.

In detection theory threshold models capture this hypothesis of discrete internal evidence states (Macmillan & Creelman, 2005). A useful threshold model that captures the basic idea of the unfolding model is a three-state model shown in Fig. 2 (cf. Wickens, 2002). The model has three discrete evidence states labeled as assurance, uncertainty, and conviction. We have adopted the labels merely out of convenience for keeping track of the three states. These latent evidence states serve a very similar role as the internal evidence in the Gaussian model with the difference being that they are discrete states (i.e., one is either in or out of the state) as opposed to a single continuous level of evidence.

According to the threshold model, after students experience a shock there is a probability α that the student enters an evidence state of conviction. Once a student enters this state of conviction, then with probability of 1.0 he or she withdraws. We have modified the three-state model in Fig. 2 to illustrate how response ratings of intent to withdraw (the structure of our data) were incorporated within this model. So in this case, if the student is in a state of conviction, then with probability 1 they "Strongly Agree" with the statement that he or she intends to withdraw. This path is analogous to the unfolding model's Path 1 where once a student experiences a shock he or she takes action consistent with a previously held script leaving without further deliberation.

Alternatively, after experiencing a shock with probability $1 - \alpha$ the student enters a state of uncertainty. In terms of the unfolding model, this would be the state of misfit where an individual's surroundings do not match his or her goals, values, or expectations (Paths 2 and 3). From this state the student decides what the best course of action would be. If we were modeling a simple binary decision to stay or withdraw, then with probability γ the student

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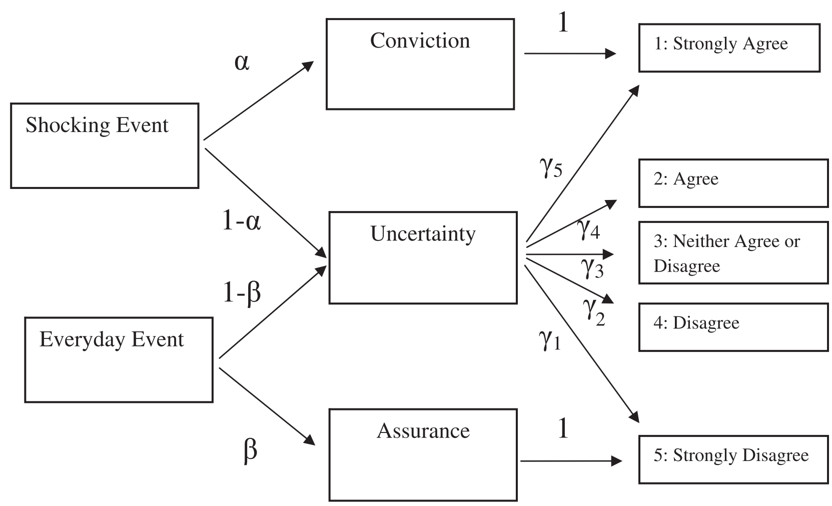

Fig. 2. A three-state model of college withdrawal decisions.

would stay and with probability $1-\gamma$ the student would withdraw. For our data, the state of uncertainty is the state from which different levels of ratings can emerge so that with probability γ_i rating i is given under the constraint that $\Sigma\gamma_i = 1$.

If a student experiences a normal event, then with probability $1-\beta$ he or she also enters a state of uncertainty. This is analogous to Paths 4a and 4b in the unfolding model where a student leaves without experiencing a shock (Table 1). Alternatively after experiencing normal events the student enters (or stays in) a state of assurance with probability β. If the student is in a state of assurance then he or she will stay with probability 1.0, or in terms of ratings, the student "Strongly Disagrees" with the statement that he or she intends to withdraw.

As the discussion of the three-state threshold model illustrates, the unfolding model gives rise to a second competing hypothesis as to the structure of the underlying decision process to withdraw:

Threshold Hypothesis: If the decision to withdraw follows the discrete paths of the unfolding model then this should result in the students' intent to withdraw data being best fit by the three-state model.

The threshold hypothesis is plausible. Besides being consistent with the process of the unfolding model, finite state or threshold models in signal detection theory instantiate this discrete-state assumption and have proven helpful in understanding aspects of memory (Batchelder & Riefer, 1990; Bayen, Murnane, & Erdfelder, 1996) as well as in psychological assessment (Batchelder, 1998; Riefer et al., 2002). Thus, comparing the fit of threshold models to the Gaussian models can help investigate the basic underlying architecture of the decision to quit.

Measuring the sensitivity of students to shocking events

Environmental factors such as the availability of social and academic activities and the affordability of student housing have long been recognized as integral in understanding student withdrawal and retention (Bean; 1985; Nora, Barlow, & Crisp, 2005). Shocks are an alternative means by which environmental factors can influence college withdrawal. But, presumably not all shocks are created equal. It seems plausible to assume that students might be more sensitive to some shocks than others.

The detection models provide a theoretically meaningful means to measure the sensitivity of students to different shocks in their academic and social environment. In traditional laboratory applications of signal detection theory, sensitivity refers to observers' discrimination between a signal and background noise. In the context of student withdrawal, sensitivity refers to the responsiveness of students quit decisions who experience a shock relative to those who only experience the background noise of "everyday" events. In the Gaussian models, the d' parameter indexes sensitivity to shocks. In the threshold models, the parameter(s) linking the event to the internal states (α and/or β) control sensitivity.

To measure the sensitivity of students to a variety of shocks, we will use empirical Receiver Operator Characteristic (ROC) curves. ROC curves plot the probability of withdrawing given an experience of a shocking event as a function of the probability of withdrawing given an experience of everyday events. To illustrate the properties of a ROC curve, Panel B in Fig. 1 plots a set of ROC curves for different hypothetical levels of sensitivity to shocks (under the Gaussian model in this example). Looking at the ROC curve for $d' = 1$, one can see that even if a response criterion is at the different locations in Panel A (a, b, c, or d), these points will still fall on the same ROC curve. Thus, a desirable attribute of d' as a measure of sensitivity is that it is independent of the response criterion students adopt. Recall that the location of the response criterion reflects factors present at the time of the response such as the costs and benefits of withdrawing. We will return to the role of the response criterion in the discussion.

Summary

In summary, we have used signal detection theory to develop competing models of the college withdrawal decision. In this paper we test whether Gaussian detection models positing an internal continuous state of evidence provide a better fit to the data than a family of threshold models positing discrete internal states of evidence. Both process-level hypotheses are consistent with some of the assumptions used to model voluntary employee turnover decisions. By fitting each of these different formal models to students' rated intent of withdrawing we can use goodness-of-fit measures to quantitatively assess how well each formal cognitive process model accounts for the data and thus by implication how well the different processing assumptions (discrete or continuous) account for the data. Moreover, the parameters of the models also provide an independent, theoretically motivated means to measure the sensitivity of students to different events that might be considered shocks. We used data collected from one wave of a longitudinal study of student performance across 10 US colleges and universities. Our analysis focused on the intentions of students to withdraw from college and was collected after the first semester of their freshman year.

Method

Sample

The data were collected in the context of a longitudinal study aimed at developing and testing alternative predictors of student performance. The longitudinal study took place in four different waves. During the first wave a total of 2771 freshman students at ten colleges and universities across the United States participated in the study during their freshman orientation on a voluntary basis. Students were deliberately sampled from participating universities that were diverse in terms of region of the country; one was in the Southwest, two were historically Black colleges in the Southeast, five were Big Ten Midwestern universities, one was in the Southeast, and one was a highly selective private Midwestern school. The numbers of participants in each of the schools ranged from 139 to 464. Precise details on the procedures can be found in Quinn et al. (2008). The data from this large-scale study have been previously published in very different formats to answer very different questions (see Schmitt, Billington, et al., 2009; Schmitt, Fandre, et al., 2009; Schmitt, Oswald, Friede, Imus, & Merritt, 2008; Sinha, Billington, Imus, & Schmitt, in press).

The measures for the present analyses were collected in the second wave near the end of students' first semester of college. A total of 2631 students from the original sample agreed to be contacted for future participation; 1234 responded to the survey in the fall (47%); and 1158 provided enough responses to be included in one or more analyses and constitute our final sample. Responses were made on an online survey. As compensation for their time, participants were given a $20 gift certificate to a major retailer and were entered into a drawing for a $100 cash prize.

The average age of the sample was just over 18 years and 66% of the sample was female. Ninety-four percent were US citizens, and 94% indicated that English was their native language. Sixty-five percent reported being Caucasian, 10% African American, 12% Asian, 6% Hispanic, and 5% other ethnicities (2% did not respond).[2] Participants were diverse in terms of intended major with over five colleges represented (e.g., business, engineering), each major comprising no more than 20% of the sample.

Materials

Intentions to withdraw

We asked students three questions regarding their intent to withdraw from their current university. First, they reported whether they intended to be enrolled at their school 6 months from the time of the survey. Second, they indicated whether they intended to transfer to a different school at or before the end of the academic year. Last, they rated their intentions to leave school and get a job at or before the end of the academic year. All responses were made on a 5-point scale (1 = *Strongly disagree* to 5 = *Strongly agree*). In our analyses we reverse coded item 1 (intent to be enrolled 6 months from the time of the survey).

Consistent with the growing trend of high levels of institutional switching (or swirling) among students (Herzog, 2005), in our sample the first two items (intent to be enrolled at their school 6 months from now and intent to transfer to a different school) were highly correlated $r = .73$, $p < .01$. The third item to withdraw and get a job was not as strongly correlated with the other two items ($r = .37$, $p < .01$ and $r = .39$, $p < .01$), for intent to withdraw in 6 months and intent to transfer, respectively). Moreover, in our first pass through the analysis, we did our analyses on each individual intent item. In general, the intent to withdraw and get a job showed very few positive results. We suspect that these null results were due in large part that in our sample 89% of the students strongly disagreed (a '1' rating) with the statement, again consistent with the high levels of institutional switching commonly observed (Borden). In comparison, both the intent to withdraw 6 months from now and intent to withdraw to transfer produced highly similar patterns of results. Thus, we decided to average responses to items 1 and 2 and for analytical convenience rounded this value to the nearest integer to form our final measure of intent to withdraw ($M = 1.9$, $SD = 0.9$). This composite measure of withdrawal has a reliability of $\alpha = .84$. In all of our analyses we report the results using this composite measure of intent to withdraw, and footnote when and where there was a divergence between results using individual items.

In detection theory, ratings (e.g., intent to withdraw) are often used as a proxy for choice (Macmillan & Creelman, 2005; Wickens, 2002). In particular, ratings provide an efficient means for estimating ROC curves and testing detection models. In our case, the ratings provide eight degrees of freedom whereas if we used a binary choice we would only have two degrees of freedom. These additional degrees of freedom aid in measuring the sensitivity of students to shocks and in testing different possible detection models.

The underlying assumption of using the rating as a proxy for choice is that the same decision process is used with the only difference being the response set available to the participant (Macmillan & Creelman, 2005). This assumption is supported by the fact that intentions are often the best—but not perfect—predictors of behavior (Fishbein & Ajzen, 1975). Employee turnover models almost invariably place intentions as the most proximal measure to the actual turnover decision (e.g., Mobley, Griffeth, Hand, & Meglino, 1979), and meta-analyses have shown that quit intentions – accounting for approximately 25% of the variance – are the single best predictor of employee turnover (Griffeth, Hom, & Gaertner, 2000; Hom et al., 1992). This is also consistent with literature on college withdrawal (Bean, 1980, 1982). Bean (2005) stated that "in every study of residential students I have participated in, the intent to leave (or stay) variable was the best predictor of actual student departure from college" (p. 218). Therefore, in all of our analyses we treat the intent to withdraw as a proxy for the choice to withdraw. In other words, in all of our analyses we are assuming students use the same cognitive process to rate their intent to withdraw as they use to decide to withdraw.

Critical events

In a later portion of the survey, participants indicated whether or not each of the 21 events listed in Table 3 "happened to me" during college. We generated a long list of critical events that might be considered shocking in terms of leading to a quit decision based on our own experiences and observations of college life as well as from two additional sources. First, a focus group ($n = 11$) was conducted with undergraduate students who were asked to identify sudden, major events that might make students withdraw or consider withdrawing. Second, an undergraduate director in charge of student petitions to drop out was interviewed in order to derive additional themes or issues regarding reasons for student withdrawal. The final list comprised 21 critical events. Sample items include "Lost financial aid" and "Death or illness of a family member." The full set of items is listed in Table 3. Only item 3 (pregnancy) was gender specific. Consequently, we only used female responses for this item; all other analyses in Table 3 collapse across genders. In the survey, self-reports of experiencing (or not experiencing) each critical event were collected well after rated intent to transfer, with a large number of unrelated intervening items being asked. This was done to minimize possible biases

[2] Although two historically black colleges were included in our sample response rates were lower at these institutions.

Table 3
ROC analyses of the 21 critical events.

Shock	N	Base rate (%)	d' (SE)	95% Confidence interval
1. Theft	1147	10.9	0.00 (0.20)	$-0.39 < d' < 0.39$
2. Assault	1131	2.9	0.05 (0.21)[c]	$-0.36 < d' < 0.46$
3. Pregnant	732	0.7	0.35 (0.42)[c]	$-0.48 < d' < 1.18$
4. Recruited by other job/institution	**1143**	**9.9**	**0.36* (0.10)[a,b]**	**$0.17 < d' < 0.55$**
5. Unexpected bad grade	**1137**	**58.6**	**0.12* (0.05)[a,b]**	**$0.03 < d' < 0.21$**
6. Roommate conflicts	**1115**	**43.2**	**0.14* (0.05)[a,b]**	**$0.04 < d' < 0.25$**
7. Lost financial aid	**1137**	**6.1**	**0.30 (0.13)**	**$0.05 < d' < 0.55$**
8. Became ill	1147	52.9	0.08 (0.05)[b]	$-0.01 < d' < 0.17$
9. Death or illness of family member	1134	18.4	0.04 (0.08)	$-0.12 < d' < 0.19$
10. Became clinically depressed	**1137**	**10.6**	**0.41* (0.10)[a,b,c]**	**$0.21 < d' < 0.60$**
11. Close friend/significant other left school	1141	8.9	0.14 (0.11)	$-0.08 < d' < 0.36$
12. Became addicted to a substance	1140	3.1	0.30 (0.20)	$-0.09 < d' < 0.69$
13. Conflict with a faculty member	1142	8.1	0.03 (0.12)	$-0.21 < d' < 0.27$
14. Came into a large sum of money	1142	5.7	0.04 (0.15)	$-0.24 < d' < 0.33$
15. Family member lost job, family in need of financial help	1141	13.2	0.00 (0.10)	$-0.19 < d' < 0.19$
16. Lost job that was needed to pay tuition	1143	2.3	0.14 (0.22)	$-0.30 < d' < 0.58$
17. Large increase in tuition/living costs	**1142**	**13.2**	**0.19* (0.09)[b]**	**$0.01 < d' < 0.38$**
18. Experienced a significant injury	1135	5.5	0.28 (0.15)	$-0.01 < d' < 0.57$
19. Became engaged or married, or entered a civil union	1137	1.7	0.00 (0.84)	$-1.64 < d' < 1.64$
20. Received a job offer	1122	15.9	0.14 (0.08)[c]	$-0.03 < d' < 0.30$
21. Was unable to enter intended major at school	1141	3.7	0.24 (0.18)[b]	$-0.11 < d' < 0.59$

Note all the reported estimates use the withdraw item collapsed across the individual items of "Intent to withdraw 6 months from now" and "Intent to withdraw and transfer." Only female response were used for item 3 (whether a person experienced a pregnancy or not).

* $p < .05$. Bolded items identify shocks for which d' was significantly different from 0.

[a] d' estimate for "Intent to be enrolled months from today" item was significantly different from 0, $p < .05$.

[b] d' estimate for "Intent to withdraw and transfer" item was significantly different from 0, $p < .05$.

[c] d' estimate for "Intent to withdraw and get a job" item was significantly different from 0, $p < .05$.

and/or item priming effects (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Results

The results section is organized as follows. Our first goal was to test the different hypotheses about the underlying process (Gaussian or threshold). But, quantitatively testing the models requires that we identify a set of critical events that count as shocks. Thus, for each of the 21 shocks, we first used the rated intent to withdraw variable to calculate the area under the ROC curve (A; Green & Swets, 1966; Pollack & Hsieh, 1969). The area under the ROC curve is an index of sensitivity that makes no assumption about the underlying decision process and thus we used it to identify a set of shocks to use in model testing. Based on these results, we next used maximum likelihood methods (described later) to fit different detection models to the data to identify a particular model that can best characterize the decision process to withdraw from a university. Finally, we used the best fitting model to measure the sensitivity of students to the 21 critical events. While the area under the ROC curves offers one measure of sensitivity, this statistic is quite conservative and tends to underestimate sensitivity (Donaldson & Good, 1996; Macmillan & Creelman, 2005).

Area under the ROC analyses of sensitivity to potentially shocking events

As a first step, we estimated ROC curves for each event using our respondents' ratings on their intent to withdraw from their college or university (collapsed across intent to withdraw 6 months from now and intent to withdraw to transfer). The basic data structure is a 2 (shock or not) $\times$ 5 (rated intent to leave) contingency table conditional on each shock. To estimate empirical ROC curves from the data, we borrowed methods that are often used to form ROC curves from confidence ratings (Macmillan & Creelman, 2005; Wickens, 2002). Again the explicit assumption is that students use the same cognitive process to rate their intent to withdraw as they use to decide to withdraw. The basic idea in estimating an ROC is that each rating (in our case, extent of agreement) is considered a choice at a different level of the response criteria (a, b, c, or d in Panel A of Fig. 1). The frequency of students withdrawing, for example, at the criterion for the intent rating of 4 is the cumulative frequency of ratings at or below 4. This was done for both the group of participants reporting a particular critical event (e.g., tuition increase) and the group not reporting a particular critical event. Using this method for each critical event we calculated four different estimates of withdrawal rates. These estimates were then used to form an empirical ROC curve. Thus, in the end, assuming homogeneity across subjects, we had 21 empirical ROC curves.

For each of the 21 shocks we calculated the model-free, nonparametric measure of sensitivity: the area under the ROC, A. The area measure increases from $A = .5$ at no sensitivity (i.e., the underlying distributions perfectly overlap) to $A = 1.0$ for maximum sensitivity (i.e., there is no overlap in the underlying distributions). The ROC curve in Panel B of Fig. 1 displays the area under the ROC for different levels of d' in the equal variance Gaussian signal detection model. Using the composite measure of intent to withdraw, two of the 21 events were significantly different from .5: (a) if a student was recruited by another job or institution ($A = .57$, $SE = .03$, $p < .01$) and (b) if a student reported being clinically depressed ($A = .59$, $SE = .03$, $p < .01$).[3] The empirical ROC curves are shown in Fig. 3 for the two shocks that had significant As.

Out of a concern that we were capitalizing on chance, we had the opportunity to run an exact replication of this study (see

[3] In the analyses at the individual item level the following results were obtained. For the intent to be enrolled at their school 6 months from the time of the survey the same two events were significantly different from .5: (a) if a student was recruited by another job or institution ($A = .56$, $p < .05$) and (b) if a student reported being clinically depressed ($A = .58$, $p < .01$). For the intent to withdraw and transfer to a different school again if a student was recruited by another job or institution ($A = .57$, $p < .05$) and if a student reported being clinically depressed ($A = .59$, $p < .01$). But, also experiencing a large increase in tuition/living costs was significant ($A = .55$, $p < .05$). Finally, for the intent to withdraw and get a job only the pregnancy item was significant ($A = .77$, $p < .05$).

Please cite this article in press as: Pleskac, T. J., et al. A detection model of college withdrawal. *Organizational Behavior and Human Decision Processes* (2011), doi:10.1016/j.obhdp.2010.12.001

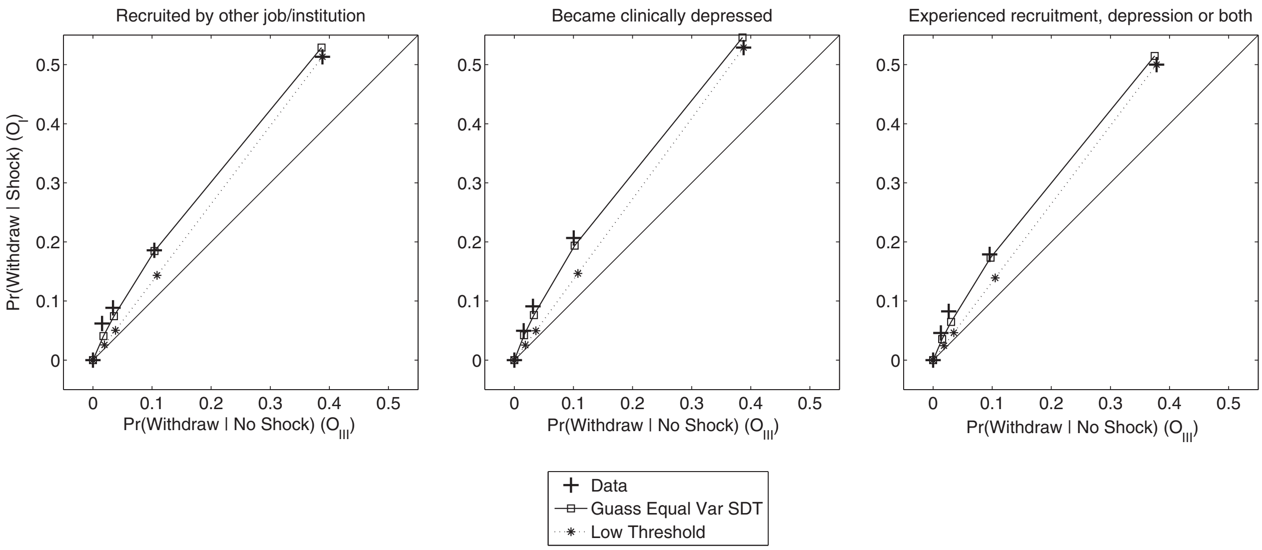

Fig. 3. The ROC curves for the two individual shocks identified with the area under the curve analyses and the collapsed variable used in model testing. The third ROC (Panel D) was calculated by collapsing across the two individual shocks and was used to identify the best fitting detection model. The functions were calculated using students' rated intent of withdrawing.

Schmitt, Billington, et al., 2009; Schmitt, Fandre, et al., 2009). Using a sample with similar characteristics and the same composite measure of withdrawal we replicated these results with clinical depression ($A = .60$, $SE = .03$, $p < .05$) and being recruited by another job/institution ($A = .57$, $SE = .04$, $p < .05$) producing significant area under the ROCs. Two other critical events (close friend or significant other left school, $A = .58$, $SE = .04$, $p < .05$; and a large increase in tuition/living costs $A = .55$, $SE = .03$, $p < .05$) also had significant *A*s in the replication study, but they were not significant in the current study so we will focus only on the depression and recruitment events in the subsequent analyses.

To increase the power of our model comparisons, we collapsed across the two shocks identified with the area under the ROC curves statistic (clinically depressed; recruited by other job/institution) and treated any individual who reported at least one of these events as experiencing a shock. The ROC for this collapsed shock variable is shown in the third panel in Fig. 3. This produced $n = 1128$ usable cases of which 19% reported experiencing at least one of the two shocks. Out of these individuals, 93% experienced 1 of the two shocks and only 7% reported experiencing both shocks. The ROC curve for this collapsed variable is plotted in panel D of Fig. 3. The area under the ROC is $A = .57$ ($SE = .02$), $p < .01$.

Detection model comparison

We used this collapsed shock variable to test the hypotheses about the underlying decision process using a model comparison method. We fit six different models to the response proportions and two baseline statistical models using maximum likelihood methods. A description of the specific models is given in Table 4.

The different detection models allow us to quantitatively test different hypotheses about the underlying decision process. The Gaussian models test the hypothesis that the student generates a continuous level of internal evidence – via perhaps a process akin to image theory's compatibility test (Beach & Mitchell, 1998) – where the magnitude of the evidence indexes how strongly the evidence points to withdrawing. The student then makes a decision by comparing the magnitude of the evidence to a criterion. The threshold models, in comparison, represent the hypothesis that college withdrawal decisions are based on discrete unobservable states, much like the discrete paths of the unfolding model (cf., Harman et al., 2007; Holtom et al., 2005; Lee et al., 1996; Lee & Mitchell, 1994). To test these different information-processing hypotheses we will use a model comparison process where each model is fit to the data and the model that best fits the data will indicate the supported hypothesis.

Within each of those sets of models, we can further constrain the parameters to test even more specific hypotheses. For instance, the Gaussian equal variance model tests the hypothesis that the distribution variances for everyday and shocking events are equal. Similarly, the low threshold model tests the hypothesis that a low threshold process, where $\alpha = 0$ in the three-state model (i.e., automatic quitting does not occur), best characterizes the decision process to withdraw. Each of these nested models and their hypotheses they instantiate were tested with a model comparison method.

To provide a better context for how well the detection models account for the data, we also estimated two baseline statistical models that assume no underlying decision process. The detection models should do better than both of these statistical models. The first baseline model is a saturated baseline model that assumes no decision process and simply uses the empirical response proportions conditional on experiencing a shock or not to calculate the likelihood of the data. The model is saturated – the number of free parameters equals the degrees of freedom ($df = 8$). As a result, the saturated model can perfectly reproduce the data. This baseline model allows statistical differences to occur between shocks, but does not posit an underlying decision process (e.g., one rates their intent to withdraw in accordance with the sample proportions). The second baseline model listed at the bottom row of Table 4 also assumes no decision process, but uses the marginal response proportions collapsed across experiencing a shock and not experiencing a shock to calculate the likelihood of the data. It, thus, has four free parameters and basically assumes no effect of shock.

The detection models were fit using maximum likelihood methods where the likelihood function for all the models is based on a multinomial distribution.[4] We used the Bayesian Information Criterion (BIC; Kass & Raftery, 1995; Raftery, 1995; Schwarz, 1978;

[4] The detection models were fit to the response proportions using Matlab®'s constrained nonlinear optimization routine based on a quasi-Newton approximation of the Hessian function.

Table 4
Summary of detection models and indices of goodness-of-fit.

Model	Hypothesis	Parameter constraints	No. free par.	BIC
Saturated baseline	No decision process. But different response proportions when responding to a shock or not. Response proportions are the observed response proportions		8	2310.82
Gauss	A shock gives rise to a continuous unobservable level of evidence which is normally distributed	Free: d'; s_{shock}; $k_{1,2,3,4}$	6	2297.49
Gauss equal variance	A shock gives rise to a continuous unobservable level of evidence. The evidence is normally distributed and variances of normal and shocking event distributions are equal	Free: d'; $k_{1,2,3,4}$ Fixed: $s_{\text{normal}} = s_{\text{shock}} = 1$	5	2292.12
Gauss no sensitivity	A shock gives rise to a continuous unobservable level of evidence. Evidence is normally distributed. The means of the distributions are the same, but the variances differ	Free: s_{shock}; $k_{1,2,3,4}$ Fixed: $d' = 0$	5	2297.41
Three-state threshold	There are three internal states (conviction, uncertainty, assurance). Our assumption is that only if one is in an uncertain state does the person respond with intermediate ratings	Free: α; β; $\gamma_{1,2,3,4}$	6	2300.28
Low threshold	There are two internal states (uncertainty and assurance). A shock puts a student into a state of uncertainty. If a student does not experience a shock then they are in an uncertain state with prob. β; otherwise they are in a state of assurance	Free: β; $\gamma_{1,2,3,4}$ Fixed: $\alpha = 0$	5	2298.32
High threshold	There are two internal states (uncertainty and conviction). A shock puts a student into a state of conviction with prob. α; otherwise they are uncertain. If a student does not experience a shock then they are in an uncertain state	Free: α; $\gamma_{1,2,3,4}$ Fixed: $\beta = 0$	5	2301.14
Constrained baseline model	No decision process. Response proportions are the same across shock and no shock. Response proportions are observed marginal response proportions		4	2330.14

When using BIC to make quantitative model comparisons the smaller values indicate better fits.

Wasserman, 2000) to make our model comparisons. The BIC is calculated for each model according to the following expression

$$BIC = -2ML_i + j_i log(n). \tag{1}$$

where ML_i is the maximum log-likelihood of model i, j is the number parameters in the model, and n is the number of observations. The model with the smallest BIC is selected as the best fitting model.[5] The number of parameters in the expression serves as a handicap for model complexity, where models with more parameters tend to over fit the data and therefore the BIC is handicapped more. As a rule of thumb, based on the BIC's Bayesian roots, a BIC difference of 2 or less is interpreted as weak evidence, 2–6 as positive evidence, 6–10 as strong evidence, and greater than 10 as very strong evidence, for the particular model (Raftery et al., 1995; Wagenmakers, 2007).

The last column in Table 4 lists the BIC value for each model. All the detection models give a better fit than either of the two statistical baseline models. This implies that a model of the decision process adds some explanatory power beyond simply a statistical description. Focusing first on the threshold models, the low threshold model ($\alpha = 0$) is the best fitting model. This is informative especially for the unfolding model. This implies that the unfolding model's Path 1 where once a person experiences a shock it is automatic that he or she will leave may not be necessary to account for the data. Finally, in accord with the Gaussian hypothesis that the Gaussian detection model better describes the college withdrawal decision process, across all models the Gaussian equal variance model is the best fitting model.

As a final model comparison method, we can also examine the fits of the models to the data. We have plotted the fits of the Gaussian equal variance model and the low threshold model to the ROC curves of the two individual shocks we identified using the area under the ROC analyses as well as the collapsed shock variable in Fig. 3. Visually, they show the fits of the Gaussian equal variance model (squares connected with a solid line) were far nearer to the actual data points (crosses) than the low threshold model (asterisks connected with a dotted line). Taking the visual inspection of the fits together with the BIC index of fit, we conclude that the model that best describes the data is the Gaussian equal variance model. This result, in turn, implies that a more precise process account for the decision to withdraw or quit is not in terms of discrete states, but in terms of a continuous level of evidence.

d′ Analyses of sensitivity to potentially shocking events

The d' parameter of the Gaussian equal variance detection model provides a measure of sensitivity to shocks that is both meaningful in terms of the underlying decision process and is more powerful than the area under the ROC estimate (see Donaldson & Good, 1996; Macmillan & Creelman, 2005). To this end, the maximum log-likelihood estimates of d' for each shock are listed in the right-hand side of Table 3.[6] The analysis revealed that students were sensitive to six critical events: (a) recruited by other job/institution; (b) unexpected bad grade; (c) roommate conflicts; (d) lost financial aid; (e) became clinically depressed; and (f) a large increase in tuition/living costs. Note some events displayed a relatively large effect size compared to others (pregnancy, became addicted to a substance), but were not significant. These events also had a low base rate of occurrence (well under 10%) perhaps contributing to the lack of a significant effect.

[5] When comparing two models (M_1 and M_2), if we assume that the prior distributions over the parameters conform to certain reasonable noninformative priors and that the likelihood of the two models are equally likely then the posterior probability of M_1 given the data can be found. For more detail see Raftery et al. (1995) and Wagenmakers (2007).

[6] Standard errors were estimated from numerical estimates of the Hessian matrix obtained from the optimization routine. For large sample sizes, taking the inverse of the element at ith diagonal position of the Hessian matrix and multiplying it by -1 provides an estimate of the variance of the ith parameter. If we take the square root of this element, then we have a numerical estimate of the standard error of this parameter.

Post hoc analyses of the accumulating effect of shocks

The Gaussian equal variance model also can be used to examine hypotheses about the relationships between shocks. For instance, one natural hypothesis is that there would be an accumulating effect of experiencing more than one shock. This is difficult to test in this sample due to the low number of individuals that reported experiencing 1 or more shocks. For example, only 16 individuals (1.4% of the sample) reported experiencing clinical depression and being recruited by another institution. Despite this limitation our modeling results suggest that there may be an accumulation effect on students' intent to withdraw. Specifically, we calculated the fit of a Gaussian equal variance model with one d' for individuals who reported experiencing either clinical depression or recruitment or both. This is the same model we estimated in the detection model comparison (see Table 4). We also fit a second more general model that had two d's: one d' for the individuals who experienced either depression or recruitment and one d' for the individuals who experienced both events. This more general model gave a substantially better fit to the data with a BIC = 2277.47 than the more constrained model with only one d', BIC = 2292.12 (see Table 4). The d' for the group experiencing only one shock (clinical depression or recruitment) was $d' = 0.26$ ($SE = 0.01$) and the d' for the group of individuals experiencing both events was $d' = 1.17$ ($SE = 0.08$). Thus, these post hoc analyses reveal that: (a) there is statistical difference between experiencing one or two shocks and (b) there is an accumulating effect of shocks on one's underlying evidence to withdraw. More generally, we think the analysis also demonstrates the ability of a formal process model to reveal and test new hypotheses.

Discussion

This paper drew from the theoretical frameworks of employee turnover and signal detection theory to develop a detection model of college withdrawal. The modeling framework offers a new perspective to college persistence models, which largely focus on how academic, social–psychological, and environmental factors ultimately predict college turnover (Aitken, 1982; Bean, 1985; Braxton & Lee, 2005; Nora, 2004; Nora & Cabrera, 1996; Tinto, 1975). In contrast, our focus has been on developing a formal cognitive model of the decision process students use to form withdrawal intentions. Besides synthesizing theory in an observable and testable form, the detection models provide independent, theoretically motivated parameters for the measurement of different factors that can contribute to withdrawal decisions. To these ends, we applied the model to a dataset collected across 10 US universities and colleges.

In terms of measuring the sensitivity of students to different shocks, the analysis identified six events that could be considered significant predictors of intent to turnover. The detection model framework was also revealing about the properties of the underlying decision process: an equal variance Gaussian model better described the data than a model based on discrete internal states. In the remaining sections of this discussion we will review the theoretical implications of these results in terms of understanding what events are particularly shocking to college students as well as the consequences of the equal variance Gaussian model and the predictions it makes.

What do the shocks tell us?

Signal detection theory (Green & Swets, 1966) offers a theoretically meaningful method to measure how sensitive students were to different potentially shocking events. To date, in terms of the general turnover literature, there has been little to no work on measuring the impact of shocks on turnover decisions. Most of the work with the unfolding model, for instance, has relied upon qualitative assessment of exit interviews of employees who have already quit, providing a post hoc explanation of the events that triggered their thoughts of quitting (e.g., Lee et al., 1996, 1999). Other work has relied on retrospective accounts of what events are shocking (Kammeyer-Mueller, Wanberg, Glomb, & hlburg, 2005). While verbal reports of information processes are an important indicator of cognitive processes, they should also be used with caution (Ericsson & Simon, 1980). The detection models and their measures of sensitivity, give a different perspective to our theoretical understanding of critical events that serve as shocks. That is, the models provide a measure of how sensitive students' withdrawal intentions are to different shocks. Moreover, the model reveals precisely how the shocks impact the decision process: the shocks change the underlying information one has on whether to withdraw. We acknowledge that even our analyses relied to some extent on self-reports of whether participants experienced a critical event or not. Nevertheless, developing and testing possible models of the decision process are a critical step for future studies that minimize this reliance even more.

Understanding what shocks students are sensitive to has applied implications. For example, the sensitivity information can be used in combination with the base rates of the shocks for improving the nature and timing of useful student interventions. Learning that students are particularly sensitive to being recruited by other jobs/institutions implies institutions may want to adjust their recruitment strategies so that they do not end after a student enrolls, but continue after enrollment. Such a recruitment strategy could potentially serve two roles: (a) make students feel sought after even after they arrive at the institution; and (b) better identify factors (e.g., jobs) that can keep students at a particular institution.

While one should always be cautious in interpreting null results, the analysis is also potentially informative in terms of what shocks do not have a large impact on the decision to withdraw and transfer. Across our analyses there were a number of events which consistently had little to no effect: theft, assault, death or illness of a family member, conflict with a faculty member, a family member who lost a job, losing a job that was needed to pay tuition, and becoming engaged. Knowing what events are not shocking is also important. For these non-shocking but critical events an institution would be best served in helping them cope with the event at hand as compared to addressing whether or not they intend to withdraw.

Relation to past turnover frameworks

The detection models of college withdrawal also give a new perspective to previous work on turnover/quit decisions. The models formally encompass March and Simon's (1958) more rational view of employee turnover decisions. Recall in March and Simon's framework the decision to quit was based on the utility individuals place on staying with or leaving their organization. This utility is in turn a function of the desire to stay and also the perceived ease of movement.

One issue with March and Simon's framework is that it did not describe the process by which these two factors ultimately impact the decision to quit. Different process-level hypotheses can be offered describing how the combination of desirability and ease of movement shape turnover decisions. The Gaussian signal detection model offers one hypothesis where the magnitude of the continuous decision variable represents the desirability of staying while the ease of movement impacts the location of the decision criterion. From this perspective, external factors such as shocks change the unobservable factor of desirability and d' measures how much these external factors impact the decision to quit. The unfolding model offers an alternative process level hypothesis regarding the role of desirability and ease of movement. In particular, the unfolding model positions decisions influenced by both of these factors in the more deliberative paths of 4a and 4b (see Table 1) (Harman et al., 2007; Holtom et al., 2005; Lee & Mitchell, 1994). However, as we have shown the data do not support the discrete paths posited by the unfolding model.

Instead the model comparison revealed that a Gaussian equal variance model provides a better account of the withdrawal intentions. In terms of the unfolding model, this result can be interpreted and used in different ways. One way to interpret this result is that it suggests the unfolding model could be modified. In principle, the result does support the assumption – as outlined earlier in the development of the Gaussian hypothesis – that a compatibility test is used in deciding to withdraw. This is at least consistent with some of the paths in the unfolding model (Lee & Mitchell, 1994). Yet, empirically while the compatibility test has received some focus in terms of the more general image theory (e.g., Beach, Puto, Heckler, Naylor, & Marble, 1996; Beach & Strom, 1989), it has received less empirical focus in terms of the unfolding model with more focus given to the possible paths employees took in deciding to quit (see Harman et al., 2007; Holtom et al., 2005; Lee & Mitchell, 1994; Lee et al., 1996).

Alternatively, the Gaussian equal variance model may also serve as a foundation for the development of other more precise process models of withdrawal decisions. For instance, a more precise process model would better model what and how attributes associated with critical and non-critical events contribute to the internal evidence in the Gaussian model. A similar approach to some extent has been taken in the literature on categorization and recognition memory (Dougherty, Gettys, & Ogden, 1999; Hintzman, 1988; Nosofsky, 1992). This process model of withdrawal decisions could also speak to the plausibility of assumptions like the equal variance assumption. While this assumption is helpful in that it leads to a parsimonious model that makes calculating measures of sensitivity simple and straightforward, it may prove to be incorrect in future studies. If we imagine that the experience of a shocking event is akin to adding a noisy signal to everyday noisy background events (everyday events), then clearly the assumption of equal variance between shocking events and normal events is false. Indeed such an unequal variance finding is consistently found in studies of recognition memory (Nelson, 2003; Ratcliff et al., 1992).

New predictions from a signal detection model of quit decisions

New predictions at multiple levels of analysis also emerge from detection models of college withdrawal. For example, while shocks are hypothesized to influence the internal levels of evidence, other factors will impact the response rule of students in terms of the decision criterion k. If we assume that the costs of withdrawing increase as students progress in college, then one would hypothesize that their decision criterion would increase so that independent of the level of the shock the criterion level of evidence needed to withdrawgets higher as tenure at school increases. For withdrawal rates below .5 – values generally reflective of actual withdrawal rates (Hendrickson et al., 2004) – the Gaussian models make an intuitive quantitative prediction: college withdrawal rates decline at a diminishing rate as tenure increases.[7,8] Fig. 4 shows a realization of this prediction for the Gaussian equal variance model. Intuition (Pantages & Creedon, 1978) and past data (Kohen, Nestle, & Karmas, 1978) support this macro-level prediction of the Gaussian equal variance model.

Not all detection models make this prediction. Threshold models generally predict a linear decrease in withdrawal rates. For example, consider the low threshold model, the next best fitting model behind the Gaussian equal variance model (see Table 4). Recall in the low threshold model a shocking event puts a student into a state of uncertainty ($\alpha = 0$ in Fig. 2), while everyday events can either put students into a state of uncertainty or a state of assurance. In the low threshold model, we assume that as tenure increases the probability γ that the student stays after entering the uncertain state increases. As the right hand panel of Fig. 4 demonstrates, this psychologically plausible assumption reveals that the low threshold model (and most other finite state models) predict a linearly decreasing withdrawal rate.[9]

Although our own data are limited in terms of looking at withdrawal rates across grade levels, data from one large Midwestern institution in our dataset is consistent with this predicted pattern where withdrawal rates were 15.5% after year 1, 9.2% after year 2, and 5.4% after year 3.[10] This curvilinear relationship is not limited to student withdrawals. Employee turnover rates also decrease at an increasing rate as employee tenure increases (Hom, Roberson, & Ellis, 2008; Weller, Holtom, Matiaske, & Mellewigt, 2009).[11] Thus, the Gaussian model provides a quantitative account of a macro-level phenomenon that appears consistent with the micro-processes of student withdrawal and employee turnover decisions.

The signal detection model also opens up a range of similar multi-level analyses that allow comparisons between college withdrawal decisions and employee turnover. For example, while males have larger withdrawal rates than females (46% vs. 40%) from 4-year colleges (Knapp et al., 2009), this pattern reverses in the workplace. Hom et al. (2008), for example, report that female managers and executives quit at a rate of 4.88% whereas their male counterparts quit at a rate of 3.20%. Obviously there are some shocks that may be specific to gender (e.g., pregnancy), which might account for the reversal between college and the workplace. For the shocks that are not gender specific, the Gaussian model offers three non-exclusive explanations for this pattern reversal: changes in sensitivity (d'), changes in bias or response criterion (k), and/or changes in base rates of shocking events. In our college sample, we found little difference between genders in terms of sensitivity. Using our collapsed shock variable, males had a sensitivity of $d' = 0.40$ ($SE = 0.14$) while females had $d' = 0.33$ ($SE = 0.09$), $z = .41$, $p = ns$. In terms of base rates, again using the collapsed shock variable, there was also very little difference between the genders. In total, 17.4% of males ($SE = 1.9$) and19.8% of females ($SE = 1.5$) reported a shock. By process of elimination, these results then suggest the explanatory factor for the gender reversal between withdrawing from college and quitting a job may rest with the response criterion. In other words, males may be more biased than females to withdraw from college due to perhaps disproportional costs of withdrawing from (and benefits of staying at) the university. But, in the workplace this bias reverses. This is an interesting place by group interaction and deserves future attention.

[7] The Gaussian equal variance model actually predicts a sigmoid relationship over the entire set of criterion values. However, if we assume withdrawal rates are generally below .5 – as empirical data suggest (see Hendrickson et al., 2004) – then for most values of d' the slope of withdrawal rates diminishes as criterion values increase.

[8] The hypothetical withdrawal rate for the Gaussian equal variance model was calculating assuming a base rate of .10 and then calculating the predicted withdrawal rate, $p(withdraw) = p(shock) * p(withdraw|shock) + (1 - p(shock)) * p(withdraw|everyday\ events)$. In the Gaussian model this was done with $d' = .5$ and then varying the decision criterion from $k = 1$ to 2.6.

[9] The hypothetical predictions for the low-threshold model in Fig. 4 were calculated setting $\beta = .3$ and varying γ from $\gamma = .24$ to $\gamma = .007$.

[10] These withdrawal rates are based on actual enrollment reports. The other universities in our sample only provided GPA data, which proved to be a fairly unreliable measure of withdrawal.

[11] As further evidence that as tenure at an organization increases one's decision criterion increases, Burton, Holtom, Sablynski, Mithcell, and Lee (2010) report that job embeddedness (which reflects organizational tenure) can buffer against the negative impact of shocks.

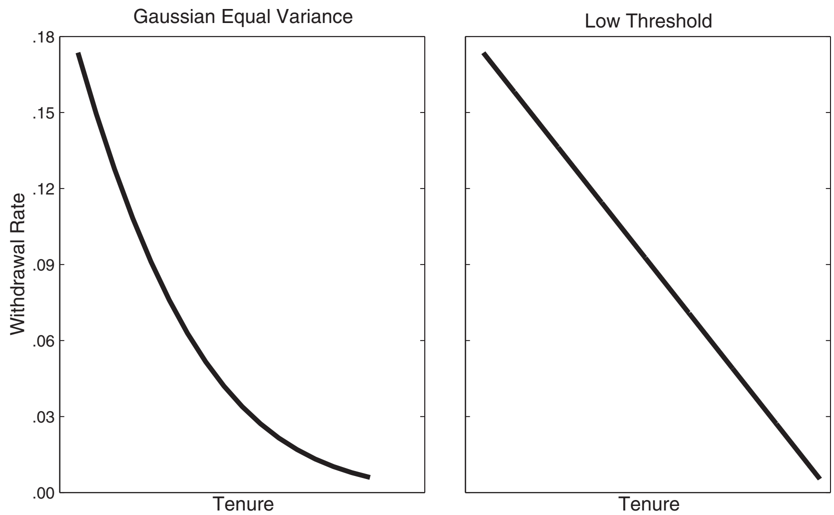

Fig. 4. Hypothetical withdrawal rate functions for the Gaussian equal variance and the low threshold models. If we assume as tenure at college increases the bias to stay increases (via k in the Gaussian and γ in the threshold model), then both models predict a decline in withdrawal rates. For withdrawal rates below roughly .5, the Gaussian equal variance model correctly predicts the decline decreases at a diminishing rate over time.

Limitations and future work

The detection model of college withdrawal provides a new perspective on college withdrawal decisions, specifically, and turnover decisions, in general. This new perspective opens several avenues of future work, some of which address limitations of the current paper. Methodologically, our large dataset with students across the United States provided an informative first step in providing a better understanding of college withdrawals. The survey methodology had a number of advantages. One advantage is that it gave us enough power to examine how sensitive students' withdrawal intentions were to some fairly infrequent events. It also afforded us the possibility to compare students who experienced a shock and students who did not. Without this methodology, a comparison between these two types of students is difficult as students who experience a shock would be, as the theory goes, withdrawing from their university.

At the same time, there are limitations to this survey approach. One is that we collected information on intentions and shocks within the same session. Although we did everything possible to minimize bias and priming (e.g., asking intentions to withdraw first, then asking a substantial number of unrelated questions before asking about shocks), these are still concerns. Our finding would be complemented by future studies that were able to compare students who withdraw to students who do not withdraw. For instance, one could use the information from this study to construct a predictive design where one focuses on the events to which students are sensitive (e.g., clinical depression or recruited by another institution) to assess whether students who experience this event actually do withdraw and at what rate and how to best describe their decision process. Nevertheless this paper is an important step in this process because it: (a) identified the events on which to focus, and (b) developed a process level model that aids in developing and analyzing the data from such a predictive design.

The detection model also raises theoretical and empirical questions about the actual decision process used to withdraw. A natural question is whether the same decision process is used in response to all shocks or whether different shocks have different associated decision processes. At the same time, one might also query whether in fact students and employees use different decision processes to quit. Throughout the paper we have largely assumed the same decision process is used across shocks and across students and employees. Our analyses support the assumption. For instance, when we fit the detection models to the individual shocks in no case did the threshold model provide a better fit than the Gaussian model. In terms of students withdrawing and employees quitting, as discussed earlier, this assumption has been made before (Bean, 1980, 1983) and in fact March and Simon (1958) suggest that all quit decisions follow the same general process.

We could, however, imagine decision processes vary between shocks and/or between educational and occupation settings. Indeed some work in judgment and decision making suggests that rather than a single decision process, agents use a range of different decision processes for different situations (Gigerenzer, Todd, & ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993; Weber & Johnson, 2009). One reason the decision process might vary is that it depends on the shocks used in the analysis. While we believe the list of 21 critical events in Table 3 is pretty encompassing in terms of possible shocks a student might face, we may be missing particular types of shocks. Moreover, the profile of shocks may differ between employees and students. Nevertheless, we believe the family of detection models we have developed can provide a powerful set of tools for exploring these possibilities.

Conclusion

In this article, we developed a framework of detection models of college withdrawal. We drew on the emerging discipline of cognitive modeling to contribute to the growing field of the computational modeling of behavior in organizations (Ilgen et al., 2000). The basic idea of formal cognitive models is to build a mathematical/computational model that describes the processes that produce a given phenomenon. In other words, the modeling venture seeks to describe the contents of the black box of cognition. The current models draw on signal detection theory to specify the decision process students use in deciding whether to withdraw from college. The models provide a theoretically grounded means to assess the impact critical events (i.e., shocks) like experiencing clinical depression or being recruited by another job or institution have on the withdrawal decision process. The models also revealed new insights for modeling withdrawal decisions. In particular, students use a parsimonious decision process where students generate an internal level of evidence for withdrawing and compare this evidence with a criterion level of evidence needed to quit.

Finally, the models also made new testable predictions regarding the effect of tenure and gender on the decision to quit school or work.

The models are of both applied and basic interest. From an applied perspective, the models provide a means to measure what events students are particularly sensitive to in leading them to withdraw from the university. This ability lends itself to helping inform institutional strategic plans to help curb withdrawal rates. From the perspective of understanding the basic decision process, the model helps connect these more everyday decisions of withdrawing to a larger experimental literature examining judgment and decision processes in the lab (see for example Ferrell & McGoey, 1980; Pleskac, 2007; Treat et al., 2001; Wallsten & González-Vallejo, 1994). Thus, the model can help serve as a bridge to help cognitive scientists scale up their models of relatively simplistic decisions that take place in the lab to account for more complex everyday decisions.

Acknowledgments

This material is based on work supported by the College Board. We thank Ruchi Sinha, Abigail Quinn, and Mark Zorzie for their input during the development of this project. We are indebted to Marcy Schafer for her careful editing of the manuscript.

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