Research Statement

Timothy J. Pleskac

My research interests are in the cognitive and decision sciences. At this intersection, I seek to develop formal cognitive theories of judgment and decision making. My aim is to (a) understand how people–with their abilities and limitations–make judgments and decisions (e.g., Pleskac, 2007; 2012; Pleskac & Busemeyer, 2010); (b) understand how deficits in decision processes are associated with unsafe and unhealthy behaviors like drug abuse (e.g., Pleskac, 2008; Wallsten, Pleskac, & Lejuez, 2005); and (c) understand how decision processes shape micro- and macro-level phenomena like college withdrawal and other turnover phenomena (e.g., Pleskac et al., 2011). I have three tracks of research

Track 1: Cognitive systems of judgment and decision making

The science of judgment and decision making has developed a reasonable understanding of when and how people make effective and ineffective judgments and decisions. But, less is known about the cognitive and neural systems used to make these judgments and decisions. For example, consider the domain of confidence judgments. If military intelligence officers give an estimate of their confidence in a yes/no prediction they have to make, then behavioral decision theory tells us that the officers will probably be overconfident. But, what we know less about is how the officers make this confidence estimate. For example, often we assume that choice and confidence are made using the exact same information. My work instead shows that choice and confidence estimates are made under different states of mind. I find that, after making a choice, people continue to accumulate evidence about their choice options; and they use this post-decisional evidence to their advantage.

We have found that this process can be modeled with a two-stage random walk/drift diffusion process (Pleskac & Busemeyer, 2010). The model provides the first process-level explanation for the complex interrelationships between choice, decision time, and confidence. An important new contribution of the model is that it reveals how the time course of confidence judgments impacts the accuracy of the judgments themselves. The dimension of time has been largely untouched and unstudied in confidence research. Yet, we would all agree that time is of the utmost importance in the forecasts we give and use. Just consider the importance of time to the military intelligence officers mentioned earlier. We find that, in fact, in some cases forecasters can strategically use time to improve the accuracy of their confidence judgments (Pleskac & Busemeyer, 2010; Yu, Pleskac, & Zeigenfuse, in prep). This ability to model the time course of confidence judgments brings to light a number of important questions regarding how time pressure impacts confidence judgments and how people should optimally balance time and accuracy in making judgments. I currently have a 5-year NSF CAREER award to investigate the prescriptive and descriptive implications of the model and more generally to study the dynamic process of confidence judgments.

Another aim of my CAREER award is to extend this drift-diffusion model of confidence to describe how people make subjective probability judgments. Descriptive theories of probability judgments generally assume accumulated evidence (support) mediates the relationship between the to-be-judged event and the judgment. This means that, when answering questions like “What are the chances that the Green Bay Packers will beat the Minnesota Vikings in football this year?” people accumulate evidence for one hypothesis (e.g., Green Bay winning) independent of the other (e.g., Minnesota winning). In a recent paper (Pleskac, 2012), I provide empirical support that evidence accumulation is a comparative process wherein hypotheses are contrasted dimension-wise, in a dependent fashion. For instance, as the competing hypotheses grow more similar on one dimension (e.g., offense), judges put more weight on the other (e.g., defense) even when the hypotheses are statistically independent of each other. The model I am developing, called Judgment Field Theory, formally describes how this comparative process unfolds via attention switching between different relevant dimensions over time, and how judges transform this accumulated evidence or belief into a subjective probability. Judgment Field Theory is well positioned to give a process-level understanding to a large range of phenomena surrounding subjective probabilities and opens new questions about how time pressure shapes forecasts in personal and professional domains.

Asking questions about how people form judgments and decisions naturally leads to questions about the neural circuitry that implements these processes. My colleague Dr. Taosheng Liu and I are working to integrate formal cognitive models and functional neuroimaging to characterize the neural circuitry of evidence accumulation. Our first paper on this topic (Liu & Pleskac, 2011) focused on perceptual decisions, but our larger goal is to apply this framework to a larger range of decisions. To this end, we have developed a novel paradigm – the Flash Gambling Task – that allows us to study this process when making risky decisions. Using this task, we have shown that computationaly an evidence accumulation process underlies risky decision making. However, unlike perceptual decisions, how people evaluate and weigh different rewards systematically distorts the decision (Zeigenfuse, Pleskac, & Liu, submitted). Our next goal is to use the task to investigate the neural circuitry involved in these processes. To this end, we have a pending grant for NIDA's ISTART program (score of 21). The aim of this grant is to investigate the neural correlates of this difference in deliberation processes as well as its role in possible decision deficits related to risky drug use.

Track 2: Using cognitive models to understand causes of risky behavior

In this track of work, I want to understand the cognitive processes underlying risky behavior outside the lab. This work is largely based on the observation that risk taking, such as substance use and risky sexual behavior, is not due to one single cognitive process. Rather multiple cognitive processes give rise to these behaviors and each process can in turn independently lead to different levels of risk taking. Of course investigating the precise properties of these cognitive processes in real world situations is very difficult. To get around this difficulty, I study the cognitive processes utilized in laboratory-based gambling tasks, like the Iowa Gambling Task (IGT; Bechara et al., 1994) or the Balloon Analogue Risk Task (BART; Lejuez et al., 2002). Or I develop my own tasks (Pleskac, 2008). These are controlled but complex gambling tasks that require respondents to make repeated risky decisions with real money at stake. Importantly, risk taking in the laboratory tasks is associated with risk-taking behavior outside the lab.

To get at the cognitive level, my colleagues and I develop and use cognitive models of the trial-by-trial decisions people make during the tasks (Pleskac, 2008; Wallsten, Pleskac, & Lejuez, 2005). These models synthesize in a formal framework how subjects process rewards, select a response, and learn from experience. We have used these models to identify the cognitive dimension(s) that are responsible for the clinical diagnosticity of the gambling tasks. For example, we find that individual differences in reward sensitivity mediate the relationship between observed risk taking and self-reported drug use. The models also reveal how processes like learning can actually impede the tasks' clinical diagnosticity (Pleskac, 2008). Finally, the models can also be used to improve the structure of the tasks to better measure the processes of interest (Pleskac et al., 2009).

My recent work with has focused on using these tasks and models to examine new questions about how people make decisions (Pleskac & Wershbale, submitted). Judgment and decision making researchers often postulate that people use one of two processes, a slow more deliberative decision process or a fast more automatic process. We have used this task to characterize how these fast automatic processes develop. Our results imply that the more automatic process can be a learned response that requires controlled and deliberate practice. To this end, we also show that some clinical populations with attentional deficits take longer to develop this automatic process. I am eager to investigate the consequences of this simultaneous interplay of automatic and controlled response processes and how it may shape behavior during other experience-based decisions.

Track 3: Experience-based decision making

In a related track of work, I am interested in developing a broader understanding about risky decision making. In this area, we typically ask people to choose between gambles like the following:

Gamble A: Win $4 with a probability of .8, otherwise win nothing.

Gamble B: Win $3 with certainty.

How would you choose? A long line or research shows that people typically choose Gamble B ($3 for certain). This choice between A and B is typically called a *decision made under risk* where the probabilities are given. My research interests have centered on *decisions made under uncertainty* where the probabilities are not given or known (e.g., lottery tickets, whether to back up your hard drive, etc.). One type of decision problem where the probabilities are not known is what we call *decisions from experience* (Hertwig et al., 2004). In this case, we replace Gamble A and Gamble B with two computer buttons. Pressing a button produces an outcome shown on the screen (e.g., "4"). No other information is provided. Thus, decision makers must sample from the options to learn about them. This situation models many real life decisions from a manufacturer choosing between two different methods for producing the same product to an employer deciding which applicant to hire. In both cases, the decision maker must infer the attributes of the options via experience.

We find that there is a distinct difference or gap between decisions made from experience and decisions made from description (Hau, Pleskac, Kiefer, & Hertwig, 2008). For example, we can make Gamble A and Gamble B above into a decision from experience and allow people to freely sample from the options and then they make one final choice for real money. If we do that we find people typically choose Gamble A. But, recall that during decisions from description people choose B. One surface level explanation for the gap is that during decisions from description people overweight rare events (e.g., the 0 outcome above), but in decisions from experience the likelihood of events are essentially taken at face value within the sample they are observed in (Hau, Pleskac et al., 2008). This gap opens up a number of interesting questions about how people make experience-based decisions such as: how memory is used (Hau, Pleskac, & Hertwig, 2009); why people tend to take small samples (Hertwig & Pleskac, 2010); and how people explore their options and ultimately make decisions (Hills, Pleskac, & Hertwig, in prep).

Sampling from uncertain options is just one way people might solve this problem of making a decision under uncertainty. I have been investigating an alternative strategy where people use their lay theories about how gambles generally work in the world to solve the problem of making a decision under uncertainty. For instance, in life we know that risk is reward: almost always the big rewards we seek to gain (and the big losses we seek to avoid) are relatively unlikely to occur. This is a normal property for gambles outside of the lab and arises due to the fact that these gambles must be financially feasible to the house, yet attractive to the player. We find that when people make decisions and they do not know the probabilities of different events happening they make use of this risk-reward relationship: they infer the probability that an event will occur from the monetary rewards that would be realized if the event occurs (Pleskac & Hertwig, in prep). This simple strategy offers a unique and new explanation for many of the phenomena that occur during decisions made under uncertainty, like the Ellsberg paradox and other related psycho-economic effects. It also exposes new questions such as how do the bets people are offered (e.g., I will bet you 2 to 1 that the Packers will beat the Vikings in the next meeting.) shape their beliefs about the events in question?

Teaching Statement

Timothy J. Pleskac

As scientists we seek to separate ideas that do work from ideas that do not. The ideas can be about how our physical world functions or how our mind operates. The ideas can also come in more applied forms like a particular medical treatment, a business practice, or an educational method. The scientific method does not discriminate. It helps us, in the words of Richard Feynman, "not fool ourselves" and not fool others in believing an idea works when it doesn't. A common objective throughout my teaching is to teach students this method and help them apply it to the problems they are interested in. Below I describe examples of how I help students forge their own scientific skills.

Problem-centered approach. The scientific method does not come with a clear road map for evaluating ideas. Rather the method is more a set of tools for blazing a trail through a forest of ideas. To help students develop their tool set, I take a problem-centered approach where I challenge students with complex, but manageable problems. For example, in my undergraduate research methods and measurement class, students are tasked with running their own small scale research project. This means they must develop a research question and design an empirical study to examine the question. Then they run the study, analyze the data, and write up the results. Thus, students learn how to formulate and analyze problems, identify a solution or even better several different possible solutions for solving the problem, and then go one step further and apply their solution.

Study past problems. Science is cumulative in the knowledge it develops and the techniques and methods it uses. For this reason, my students and I study the problems others have faced and how they solved them. This means, for instance, in my graduate course on higher order cognitive processes instead of studying secondary review chapters or articles, we read, study, and deconstruct, primary research articles. These are the articles in fields like categorization, memory, judgment and decision making, neuro-economics, and reasoning, that have driven the marketplace of ideas in our field. By focusing on these papers, students learn by example and learn how to evaluate the ideas that we think work and ideas we now believe do not work.

Study science in action. A final principle that drives my teaching is that we learn the process of science best by seeing it in action. For example, in my graduate course on the nature and practice of cognitive science we study the current cognitive science being conducted by faculty at Michigan State University. I tell my students to act as if we have adopted the research of the faculty as our own. We read the papers that have influenced their work. We read their own work, and when possible their working papers. And we meet, discuss, and debate, the ideas with the faculty themselves. Thus, besides getting to see science in action (before it is polished and refined), my students and I also gain a greater understanding of the research going on around us.

The effectiveness of my approach can be measured in quantitative and qualitative forms. Though perhaps the most rewarding for me are the less measurable outcomes. I take pride in seeing the impact of my teaching on the papers, theses, and dissertations that are written and more generally its impact on the community of scholars around me.