EDITOR'S COMMENTS

Information Systems Research and Behavioral Economics

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Because of its very nature, and reinforced by the compartmentalization of our research institutions, our discipline has evolved in segmented ways along the various reference disciplines. One of the biggest division lies along the lines of "behavioral information systems" versus "economics of information systems," as if these are completely orthogonal subfields. In my last editorial, I tried to point out that the different IS approaches are actually very close in many aspects, and that there are great opportunities for intradisciplinary IS research. Here I proceed with this general theme, focusing on the growing field of behavioral economics and its connection with IS research.

In the first chapter of their excellent book *Advances in Behavioral Economics*, Camerer and Loewenstein (2004) open the first paragraph with the following sentence: "Behavioral economics increases the explanatory power of *economics* by providing it with more realistic *psychology* foundations." Many of the insightful developments of behavioral economics are about incorporating cognitive principles to how economists approach decision making by individuals.

Much of what the IS field is about relates to information processing for decision making. With the advent of the Internet and all its evolving technologies, the decision-making IS environments have proliferated and expanded in complexity, reaching billions of individuals and consumers. These environments are characterized by increasing information richness and interactive decision making, often resulting in economic transactions: crowdsourcing and collective intelligence, electronic marketplaces, personalization and recommendation systems, synthetic and virtual environments of augmented reality, games and gamification, just to name a few.

In addition, embedded in these environments are the important issues of privacy, trust, and security, which are fundamentally connected to both behavioral and economic aspects. Behavioral economics methods can bring enormous potential to inform and complement IS research. And, very importantly, due to the information richness and complexity of these environments, IS researchers, who have deeper understanding of these environments than anybody else, can contribute back to advance the field of behavioral economics.

In much of what follows, I draw heavily from Camerer and Loewenstein. Their book provides a great introduction to the field of behavioral economics connecting past efforts to future opportunities.

Historical Perspective

How do two disciplines that were separated through most of the 20th century find common ground to open new research horizons? At the turn of the 20th century, the discipline of economics went through the neoclassical revolution, built on assumptions about rationality of human behavior—the homo-economics. It led to the belief by economists that economics was like a natural science, with the concept of utility and its mathematical treatment forming its foundation. Although there was recognition that cognitive factors needed to be somehow incorporated in the make-up of utility, economists at the time did not value psychology, then an emerging discipline, to be "scientific enough" to come to help.

Neoclassical economics, based on utility maximization, equilibrium, and efficiency, continues to be widely taught and used. Its theoretical framework provides researchers ways of approaching and modeling the economic behavior of individuals, firms, and economic entities. Its principles and concepts provide ways of generating testable hypotheses for explanatory research. It also provides a platform for deriving refutable predictions through a rigorous scientific lens. Neoclassical economics has provided the foundation for the Economics of Information Systems, a very vibrant area of the IS field today.

Toward the second half of the 20th century, researchers like Herbert Simon and Harvey Leibenstein started to write about bounds of the rationality of the neoclassical approach and the importance of considering cognitive factors. Concomitantly, work by Ellsberg (1961), Markowitz (1952), and Strotz (1955) showed anomalies with the neoclassical concepts of subjective expected utility and exponential discounting. By the fourth quarter of the century, some economists (and psychologists) turned to replicable experiments to further detect anomalies with expected utility and discounted utility (Kahneman and Tversky 1979; Lowenstein and Prelec 1992).

Interesting developments were also taking place in the field of Psychology starting around 1960. The metaphor of the brain as an information-processing device replaced the behaviorist conception of the brain as a stimulus-response machine. This led to interest in topics such as decision making and problem solving, which led psychologists to visit the economics concept of utility. In their seminal paper, Kahneman and Tversky introduced prospect theory and decision making under risk, documenting violations of expected utility and, using psychological principles, proposed an axiomatic theory to explain the violations. The work by these psychologists was published in the top economics journal, *Econometrica*, and we all know that Kahneman was awarded the Nobel Prize in Economics in 2002 (Tversky had passed away by then).

Preference Building Effects

Behavioral economists have shown that preferences are not the clear-cut set of preference curves microeconomics teaches us. They are extremely context-dependent and are subject to strong cognitive effects or biases. When making decisions, people go through a process of "building" their preferences. Framing, anchoring, and endowment are some of the cognitive biases that have been identified, which heavily influence the construction of preferences.

Framing

The way choices are presented (framed) to individuals often determines the preference that is elicited. The classic example comes from Tversky and Kahneman (1981), in which participants of a study were asked to choose between two treatments for 600 people affected by a deadly disease. Treatment A would result in the death of 400 people. With treatment B, there was a 33 percent chance that no one would die and a 67 percent chance that everyone would die. The way the options were framed to the participants varied. In the "positive" frame people were shown the number of saved lives by treatments A and B, and in the "negative" frame people were shown the number of lost lives in each treatment. With the positive framing, treatment A was chosen by 73 percent of the participants, while in the negative frame it was chosen by only 22 percent, despite the fact that they are absolutely equivalent.

Anchoring

This effect relates to how the mind is biased by first impressions. Anchoring occurs when individuals use an initial piece of information to make subsequent judgments. The initial piece may or may not be related to the decision at hand. Tversky and Kahneman (1974) demonstrated this effect by first asking individuals to spin a wheel with numbers between 0 and 100. Subsequently they asked the individuals to guess the number of African nations in the United Nations. Although the wheel spin was obviously random, the participants' guesses of the number of African nations was highly influenced by the wheel's spin.

Obviously, anchoring is a common artifact used by salespeople and smart negotiators, where a starting point is suggested to anchor the process.

Endowment

Classical economic theory asserts that the value a person attaches to a good doesn't depend on its ownership by the person. In other words, the willingness to pay (WTP) for a good should be equal to the willingness to accept (WTA) if property ownership has been established. There is plenty of evidence that ownership or current endowment has a big impact on how people valuate the good. In general, people dislike losing an item more than they like acquiring it. There are several documented studies that attest to the existence of the endowment effect, including the classic mug experiment conducted by Knetsch (1992).

Behavioral Economics and IS Research (1)

Recommendation and Personalization Systems

These systems are designed for consumers to overcome their cognitive limitations when making choices in IT-mediated environments. Ironically, by and large they have ignored the cognitive biases that come into play in decision-making. IS research has either focused on the technical aspects of such systems (e.g., Adomavicius et al. 2011) or the economic impact of recommendation systems on sales (e.g., Fleder and Hosanagar 2009). The massive amounts of information available to consumers at the decision point can lead to information overload, which can result in greater reliance on heuristics and greater susceptibility to biases in economic decision making. Vendors or providers of services also face the problem of having to analyze in real time massive amounts of information and tend to ignore the cognitive bias effects on consumers. There is a huge opportunity here for combining IS research methods (explanatory, predictive, experimentation) with behavioral economics principles to shed light on the issues and inform design science research.

Online Actions and E-Marketplaces

A great deal of IS research has focused on online auctions and marketplaces. IS researchers have contributed to the economics literature by challenging traditional assumptions of auction theory, for example, by identifying heterogeneity in bidding and participation behavioral patterns (Bapna et al. 2004). Online auction research can be further expanded by exploring cognitive biases introduced by the way information is presented in the auction sites, framing from available information from other sites and search engines, as well as the endowment effect present during auction negotiations. In these environments, observational data can be utilized to measure loss aversion effects. E-marketplaces continue to evolve, and behavioral economics can inform the design of such platforms.

Loss Aversion and Prospect Theory

The endowment effect is a good example of biases related to loss aversion. These are explained very well by prospect theory (Kahneman and Tversky 1979): the disutility of loss of x is worse than the utility of an equal size gain of x. This is shown in the classic depiction of the value function around the reference point that defines the losses region and the gains region.

The slope and the curvature of the function in the two regions represent how sensitive individuals are to losses and gains, with clear impact of the loss aversion bias.

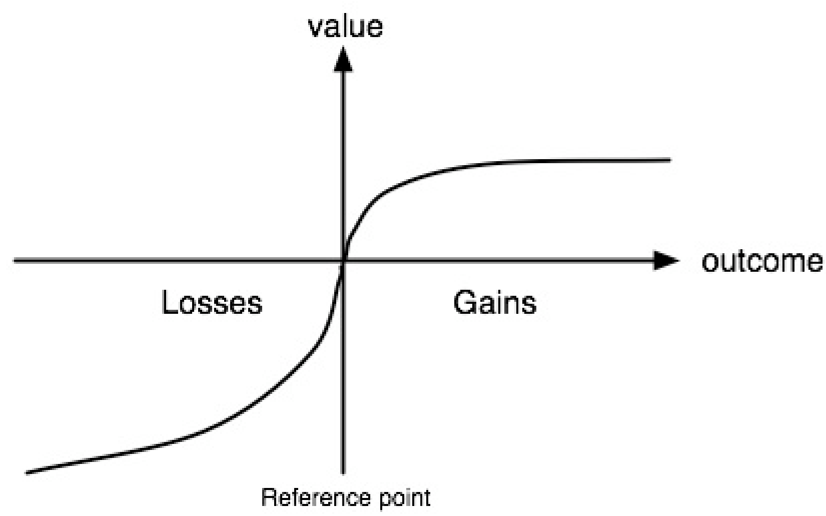

Figure 1. The Value Function

Behavioral Economics and IS Research (2)

Collective Intelligence and Gamification

Fast evolving Internet technologies have brought about a variety of new applications, marketplaces, and business models, in which the "crowd" plays an important role. Examples of the collective intelligence (Malone et al. 2010) sites are in the areas of knowledge exchange, innovation and creativity, market for services, reviews, and opinions. Typically there are contributors and consumers in theses two-sided platforms who engage in social interactions and economic transactions. User participation behavior in such environments is influenced by several factors, including economic incentives, individual quest for recognition, technology response, and social interactions. Understanding specific participation behavior is fundamental to the sustainability of the different applications. Behavioral economics can be employed in a variety of ways.

For example, to maintain engagement by participants, many sites have resorted to gamification ideas, one of which relates to giving "badges" or certifications to different levels of voluntary contribution.

These certifications can be seen as reference points of achievement or goals. Heath et al. (1999) have shown how the same principles of prospect theory can be applied to the goal setting to model the contribution behavior before achieving the goal (losses area) and after achieving the goal (gains area). In the specific environment of a question–answer knowledge exchange online community, Goes et al. (2013) have recently tested goal setting hypotheses based on prospect theory and identified ways to improve the design of the badging system as a motivator for contribution.

Time Discounting

Economics and finance have dealt with the issue of how to compare costs and benefits that occur at different points in time by using the idea of a constant discount rate that is applied in a decreasing exponential rate to values in the future.

What behavioral economists have found in laboratories and through observational data is that, in reality, the discounting follows more a hyperbolic function rather than an exponential one. Thaler (1981), Benzion et al. (1989), and Holcomb and Nelson (2002) have all shown through experiments that discount rates fall with time duration, and Prelec and Loewentein (1991) explicitly showed the immediacy effect that discounting is more dramatic in delayed time periods that in immediate time periods, corroborating the notion of an hyperbolic decline.

Behavioral Economics and IS Research (3)

Privacy and Security

When it comes to security and privacy, IS researchers have long demonstrated that individuals exhibit a dichotomous attitude toward the issues (for examples, see Chellappa and Sin 2005; Culnan 1993; Hann et al. 2007). While most individuals are genuinely concerned about security and protecting their privacy, they don't act appropriately to do so. For example, individuals are willing to trade off privacy for convenience, or bargain the release of very personal information for immediate rewards such as coupons or prizes. Acquisti (2004) and Acquisti and Grossklags (2004) have used the principles of hyperbolic discounting from behavioral economics to explain this dichotomy.

Behavioral economics as it stands today is a collection of tools and ideas, a subset of which are covered above. It also makes use of a variety of methods. Initially the discipline relied solely on experiments, but then started to test the early findings against observational data. IS researchers are experts in collecting and assembling large observational datasets off Internet applications. These datasets provide a valuable source for testing and advancing behavioral economics theories. Field experiments provide a middle ground between labs and observational data; the Internet and its various IT-mediated environments provide great opportunities for field experiments.

Behavioral economics has reinforced the point that the *context* matters in how the cognitive effects influence the choices. The context is usually associated with how information is presented, and is the reference point of the decision maker in terms of evaluation of losses and gains. Context in IS environments is much more complex than in the environments that the discipline of behavioral economics has studied. That makes it very exciting for us when we realize the tremendous potential that lies ahead.

Finally there are two important and relatively unexplored directions along which behavioral economics and IS can travel together. IS environments have become *social* environments. Adding the social dimension to the judgment and decision context has become essential. Measuring social influence has received a good deal of attention recently in IS research (Aral and Walker 2011). The second direction is provided by neural sciences. NeuroIS is growing and is demonstrating potential to bring explanatory power to cognitive effects in economic decision making (Dimoka et al. 2012).

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