Behavioral supply management: a taxonomy of judgment and decision-making biases
Craig R. Carter
College of Business Administration, University of Nevada, Reno, Nevada, USA, and
Lutz Kaufmann and Alex Michel
WHU – Otto Beisheim School of Management, Vallendar, Germany

Abstract
Purpose – The purpose of this paper is to review and integrate the extensive literature base which examines judgment and decision-making biases, to introduce this literature to the field of supply management, to create a valid, mutually exclusive, and exhaustive taxonomy of decision biases that can affect supply managers, and to provide guidance for future research and applications of this taxonomy.

Design/methodology/approach – The authors use a qualitative cluster analysis, combined with a Q-sort methodology, to develop a taxonomy of decision biases.

Findings – A mutually exclusive, and exhaustive taxonomy of nine decision biases is developed through a qualitative cluster analysis. The Q-sort methodology provides initial confirmation of the reliability and validity of the cluster analysis results. The findings, along with numerous examples provided in the text, suggest that supply management decisions are vulnerable to the described biases.

Originality/value – This paper provides a comprehensive review of the judgment and decision bias literature, and creates a logical and manageable taxonomy of biases which can impact supply management decision making. The introduction and organization of this vast extant literature base provides a contrasting perspective to much of the existing supply management research, which has incorporated the assumption of the rational agent, or what is known in the economics literature as homo economicus. In addition, the authors describe the use of qualitative cluster analysis and the Q-sort methodology, techniques which have been used rarely if at all in within the field of supply chain management.

Keywords Decision making, Supply chain management

Paper type Literature review

Introduction
The supply chain management field has tested a wide range of frameworks and models which have relied on the assumptions of neoclassical economic theory, the new institutional economic theory, and in particular transaction cost economics (Grover and Malhotra, 2003; Halldórsson and Skjøtt-Larsen, 2006; McNally and Griffin, 2004; Rindfleisch and Heide, 1997). The use of these theories has helped to significantly enrich the a priori theoretical and grounded frameworks which have been developed in our field. However, these theories, and the extant supply chain management research, have focused primarily on the efficient configuration of processes or the allocation of resources relying on the assumption of “homo economicus” – the belief that individuals are capable of rational decision making and are motivated by self-interest
to obtain the highest possible outcomes of predetermined goals (Simon, 1955). Yet there is abundant evidence that individuals often violate the rationalistic paradigm in economics, thus leading to suboptimal results (Simon, 1957; Zajonc, 1968; Kahneman and Tversky, 1972, 1979; Fischhoff et al., 1978; Thaler, 1985; Bazerman, 1998).

These violations of the assumptions of rationality can in fact be systematic, particularly under conditions of uncertainty (Kahneman and Tversky, 1979; Kahneman et al., 1982). However, research concerning behavioral and non-rational aspects of supply chain management in general, and supply management in particular, has been almost non-existent since the field of supply management began to develop as an academic discipline in the 1960s (Wind, 1968; White, 1979; Cohn and Tayi, 1990; Liang and Stump, 1996; Gao et al., 2005). Given the increasing complexity and dynamism of supply chain management and more specifically supply management (Kaufmann and Carter, 2006), and the over reliance of these fields on theories which assume rational agents, an opportunity exists to address this gap in the literature. Specifically, the purpose of this paper is to address this omission through an examination and integration of literature from the fields of economics, psychology, and human judgment and decision making, in order to answer the following research questions:

**RQ1.** What main judgment and decision biases have been described in the extant literature and how can they:

- **RQ1a.** Be logically structured.
- **RQ1b.** Be applied to the field of supply management?

**RQ2.** What are the future research directions associated with integrating human judgment and decision-making theory into the traditional theoretical paradigms of the supply management field?

In the next section, we review the above literature bases, along with attribution theory, cognitive dissonance theory, decision theory, and principal agent theory and present a comprehensive list of 76 decision biases identified in the literature. We then present the results of a qualitative cluster analysis and Q-sort methodology used to place these decision biases into a more manageable group of nine categories. Afterwards, we describe these nine categories in detail, and discuss supply management tasks which may be significantly influenced by these decision biases. Lastly, we consider the future research implications of our review and analyses.

**Literature review**

Samuelson (1938) formulated the basis for a normative theory of decision-making in economics, when he defined utility as the sum of choices reflected in an individual’s behavior. Within his work *Foundations of Economic Analysis* (Samuelson, 1947) he later defined several assumptions about an individual’s behavior, which still build the nucleus of the movement today known as neoclassical economics: individuals must be informed about all available alternatives, they must have correct expectations about the future consequences of current decisions, and they must be governed by self-interest and rationality using information in a systematic and logical manner.
Simon (1955, p. 99) later described the perfect rational or economic man (home economicus) on this basis as a man who:

... is assumed to have knowledge of the relevant aspects of his environment which, if not absolutely complete, is at least impressively clear and voluminous. He is assumed also to have a well-organized and stable system of preferences, and a skill in computation that enables him to calculate, for the alternatives of action that are available to him, which of these will permit him to reach the highest attainable point on his preference scale.

These assumptions were not only associated with the concept of homo economicus, but were also largely incorporated into game theory and expected utility theory (von Neumann and Morgenstern, 1947), subjective expected utility theory (Savage, 1954), and the theory of rational expectations (Muth, 1961; Lucas and Prescott, 1971).

Simon (1955), however, also criticized the concept of homo economicus in economic theory, stressing that uncertainty and bounded rationality exist in decision-making. Kahneman and Tversky (1973, 1979) later showed that human decisions can systematically depart from those predicted by standard economic theory, thereby "laying the foundation for a new field of research," (Royal Academy of Science, 2002). On this basis, many researchers have enriched economic theory using insights from cognitive psychology to explain human behavior which goes beyond the rationality assumptions of neoclassical and new institutional economic theory. These researchers have found that individuals may fail when it comes to judging probabilities, making predictions, or otherwise attempting to cope with uncertain decision environments in economics (Fischhoff, 1982b; Hogarth, 1987; Thaler, 2000). Simon (1957, p. 198) argued that:

... the capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world – or even for a reasonable approximation to such objective rationality.

Despite many prominent and acknowledged researchers arguing for intensifying economic research on human decision-making (Thaler, 2000; Kahneman, 2003; Frey and Stutzer, 2002), there are some voices of criticism. Some economists believe that violations of individual rationality do not necessarily refute the aggregate predictions of standard economic models that assume full rationality of all agents (Fama, 1970), as these individual deviations are random in nature. However, decision biases have been shown to have systematic patterns even in the aggregate (Kahneman et al., 1982; Einhorn and Hogarth, 1981). Another common argument is that even if individuals are irrational at times, they will learn from their mistakes. While market experience can diminish anomalous behavior in some cases (List, 2003), a number of biases are very robust to individual learning in markets (Camerer, 1987, 1992; Ganguly et al., 2000). Furthermore, it is often argued that rational agents will drive the irrational agents from the market, but this argument is not very convincing as a reduction in the quantitative weight of irrational traders is not even guaranteed in financial markets (DeLong et al., 1991). Haigh and List (2005), for example, document that professional traders from the Chicago Board of Trade are more prone to myopic loss aversion than ordinary students. In this context, Tversky and Kahneman (1986, p. 252) state that observed deviations of actual behavior from the normative models of decision-making are
“too widespread to be ignored, too systematic to be dismissed as random error, and too fundamental to be accommodated by relaxing the normative model.”

Several fields in business, including finance (Shiller, 2003; Shefrin, 2000), marketing (Backhaus and Koch, 1985; Nicosia and Wind, 1977), and accounting (Birnberg and Shields, 1989; Colville, 1981), have already begun to see research which has integrated the belief that human decision-making involves biases: in other words systematic deviations from the standard assumptions of the rational paradigm in economics. The study of these biases has been referred to as “the psychology of decision-making” (Beach and Connolly, 2005) and “judgment and decision-making” (Yates, 1990) in industrial and organizational psychology and management, and “behavioral finance” (Thaler, 1993) in finance.

While some early supply management research examined “emotional buying in industrial markets” (James, 1966), “industrial source loyalty” (Wind, 1970), and “stereotype perceptions” of suppliers’ countries (White, 1979), the extant supply management research does not address decision biases in a direct and systematic manner. Thus, an explicit acknowledgement of these biases, and an incorporation of decision biases into empirical models is largely lacking in the field of supply management. Within the current paper, the authors refer to this term as “behavioral supply management” (BSM), and define BSM as the study of how judgment in supply management decision-making deviates from the assumptions of homo economicus. The first step in correcting the negative influence that these biases can have on the decision-making process is to better understand those biases. In the next section of the literature review, we introduce and describe 76 biases identified through a review of a broad array of literature from the fields of economics, psychology, and organizational decision-making.

Overview of decision biases
As suggested by Simon (1955, 1956, 1957), limitations in information gathering, computing abilities, and a limited memory (Miller, 1956; Slovic and Lichtenstein, 1971; Arrow, 1986; Nordstrom et al., 1996) do not allow individuals to examine all possible alternatives in a complex decision environment under uncertainty and thus force decision makers to use simplifying decision strategies or heuristics (Tversky and Kahneman, 1974; Hogarth, 1987). The application of heuristics can be a rational act, but can also lead to unwarranted deviations from the assumptions of rationality (Tversky and Kahneman, 1986); alternatives may be disregarded and a “satisficing” alternative rather than an optimal solution may be accepted, event probabilities may be evaluated over-optimistically or over-pessimistically, or outcomes may just be evaluated erroneously.

A comprehensive literature review in the fields of economics, psychology, and organizational decision-making revealed a large number of decision biases, using many different labels or terms for each. A number of researchers have examined several of these biases simultaneously (Chapman and Chapman, 1969; Slovic et al., 1977; Sage, 1981; Remus and Kottemann, 1986; Hogarth, 1987; Yates, 1990; Heath and Tindale, 1994; Keren, 1996; Bazerman, 1998; Arnott, 2002). Many more researchers discuss single decision biases (Staw, 1976; Fischhoff, 1982a; Taylor and Thompson, 1982; Pitz and Sachs, 1984; Samuelson and Zeckhauser, 1988; Keren, 1990; Dawes and
Mulford, 1996; Rabin and Schrag, 1999; Lauriola and Levin, 2001; Boynton, 2003; Statman, 2005).

A systematic review of the literature revealed a total of 76 differently named decision biases or sources of decision biases. These biases were identified through keyword searches in the ABI/Inform and EBSCOhost databases. Search conditions included the behavioral terms anomaly, behavior, bias, cognition, decision, perception, rational, risk, and uncertainty. Each of the identified decision biases is listed in Table I, along with a description of the bias and corresponding, sample references. An examination of the biases displayed in Table I suggests that there are several similarities, and possible overlap, among many of the biases, despite being assigned different names by different researchers.

Given the large number of decision biases identified in the reviewed literature and shown in Table I, a taxonomy (Hambrick, 1984; Doty and Glick, 1994) is necessary to clarify the relationship between different influences of categories of biases on decision-making and at the same time consolidate knowledge in the area in a comprehensive way. To be scientifically valid, such a taxonomy should be internally consistent and not confuse different levels of abstraction within the classification. These objectives can be accomplished through clustering, which consists of the categorization of objects into groups or subsets by identifying similar characteristics of those objects (Green et al., 1967; Saunders, 1980) so that data in each subset share common traits and clearly differ from other subsets (Nairn and Bottomley, 2003).

While some researchers have attempted to create classification schemes of decision biases, all of the existing categorizations are based on subjective groupings, and none are mutually exclusive and exhaustive. For example, Tversky and Kahneman’s (1974) categorization of decision biases is not comprehensive, as some major decision biases are missing such as biases regarding persistence. Remus and Kottemann (1986) developed another multi-level categorization of biases from an information systems perspective; however, some biases appear in multiple levels within their classification. One of the most comprehensive and cited classifications of decision biases is that of Hogarth (1987), who categorizes biases according to which component of his model of human judgment they may be related. However, Hogarth does not apply a systematic methodology in creating his categorization, and some biases are listed more than once while others are absent from the classification.

Several other researchers also provide categorizations of decision biases (Slovic et al., 1977; Einhorn and Hogarth, 1981; Pitz and Sachs, 1984; Isenberg, 1984; Schwenk, 1988; Keren, 1990; Bazerman, 1998; McFadden, 1999; Arnott, 2002), however, these classifications suffer from the same weaknesses as those discussed above: a lack of systematic methodologies in creating the categorizations, and a lack of mutual exclusivity and exhaustiveness. To support further research in the fields of economics, psychology, and managerial decision-making, and to more effectively introduce these biases to the supply management discipline, we next develop a taxonomy of these decision biases using a systematic, scientifically valid methodology which results in a classification which is both mutually exclusive and exhaustive.

**Methodology**

Our data set consisted of the descriptions and definitions of the 76 decision biases, and the authors employed qualitative data analyses to cluster these biases. To ensure the
<table>
<thead>
<tr>
<th>Bias/source of bias</th>
<th>Description</th>
<th>Selection of references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attenuation</td>
<td>Decision makers tend to simplify a decision-making situation by ignoring or discounting the level of uncertainty</td>
<td>Hogarth (1987, p. 132), Beer (1995, p. 73) and Stoker (1996, p. 58)</td>
</tr>
<tr>
<td>Aversion to ambiguity</td>
<td>Decision makers dislike ambiguity about the probability law of outcomes of their decisions</td>
<td>Lauriola and Levin (2001, p. 108) and Zengjing and Epstein (2002, p. 1404)</td>
</tr>
<tr>
<td>Aversion to regret</td>
<td>Mental error that can affect decision-making in advance is an excessive focus on the potential feelings of regret at having made a poor decision (or a “good” decision that turns out poorly)</td>
<td>Shefrin and Statman (1985, p. 782, 1995, p. 32) and Statman (2005, p. 18)</td>
</tr>
<tr>
<td>Bandwagon effect</td>
<td>Tendency to do (or believe) things because many other people do (or believe) the same</td>
<td>Farrell and Shapiro (1994, p. 150) and Lee and Chan (2003, p. 97)</td>
</tr>
<tr>
<td>Base rate</td>
<td>Base rate data tends to be ignored in judgment when new or other data is available – generally abstract information will be ignored at the expense of concrete information</td>
<td>Christensen-Szalanski and Bushyhead (1981, p. 928), Joyce and Biddle (1981b, p. 325), Tversky and Kahneman (1982, p. 153), Bar-Hillel, 1990, p. 201 and Kleiter et al. (1997, p. 25)</td>
</tr>
<tr>
<td>Belief</td>
<td>The tendency to base assessments on personal beliefs while ignoring on-hand probabilities</td>
<td>Lynn and Williams (1990, p. 336) and Morley et al. (2004, p. 666)</td>
</tr>
<tr>
<td>Chance</td>
<td>A sequence of random events can be mistaken as representative</td>
<td>Lopes and Oden (1987, p. 392), Aytton et al. (1989, p. 221, 1991, p. 223) and Hastie and Dawes (2001, p. 153)</td>
</tr>
<tr>
<td>Commitment (escalating commitment)</td>
<td>Once decision makers make a commitment to a person or course of conduct, they may consistently adhere to that commitment even if later confronted with facts suggesting that the commitment is a bad choice</td>
<td>Schwenk (1984, p. 117) and Brockner et al. (1986, p. 109)</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Bias/source of bias</th>
<th>Description</th>
<th>Selection of references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completeness</td>
<td>The perception of an apparently complete or logical data presentation can prematurely lead to stopping the search for more information</td>
<td>Fischhoff et al. (1978, p. 332) and Hogarth (1987, p. 218)</td>
</tr>
<tr>
<td>Concorde fallacy</td>
<td>The British and French Government continued to fund Concorde even after it became apparent that it would not be turned profitable</td>
<td>Williams (1986, p. 243) and Arkes and Ayton (1999, p. 591)</td>
</tr>
<tr>
<td>Confirmation</td>
<td>Decision makers tend to seek confirmatory information and to exclude the search for disconfirming information</td>
<td>Fischhoff and Beyth-Marom (1983, p. 257), Einhorn and Hogarth (1986, p. 227) and Russo et al. (1996, p. 102)</td>
</tr>
<tr>
<td>Confirmation evidence</td>
<td>Tendency to search for or interpret information in a way that confirms one's preconceptions</td>
<td>Hammond et al. (1998, p. 52) and Berri and Eschker (2005, p. 798)</td>
</tr>
<tr>
<td>Confirmatory</td>
<td>Decision makers tend to misinterpret ambiguous evidence as confirming their current hypotheses</td>
<td>Higgins and Bargh (1987, p. 398), Schrag (1999, p. 39) and Idson et al. (2004, p. 160)</td>
</tr>
<tr>
<td>Contrast</td>
<td>The enhancement or diminishment of a weight or other measurement when compared with recently observed contrasting data</td>
<td>Hogarth (1987 p. 218), Highhouse et al. (1996, p. 95), Stapel and Koomen (1998, p. 132) and Shapiro and Spence (2005, p. 225)</td>
</tr>
<tr>
<td>Correlation</td>
<td>The probability of two events occurring together can be overestimated by a mistaken belief that these events covary when they do not</td>
<td>Golding and Rorer (1972, p. 249), Tversky and Kahneman (1973, p. 207, 1974, p. 1128) and Alloy and Tabachnik (1984, p. 113)</td>
</tr>
<tr>
<td>Country of origin</td>
<td>An alternative may be chosen only because it is near to home</td>
<td>Ahmed et al. (1994, p. 323), Quester et al. (2000, p. 479) and Andersen and Chao (2003, p. 339)</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Bias/source of bias</th>
<th>Description</th>
<th>Selection of references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultural</td>
<td>National and regional culture of other markets are often excluded and thus effectiveness of decisions often undercut their potential</td>
<td>Meernik <em>et al.</em> (2005, p. 693) and Pauleen and Murphy (2005, p. 21)</td>
</tr>
<tr>
<td>Desire</td>
<td>A decision maker tends to be overly-optimistic in evaluating the probability of a desired event or outcome</td>
<td>Budescu and Bruderman (1995, p. 109), Olsen (1997, p. 65), Friedman and Leslie (2004, p. 547) and Morse (2006, p. 42)</td>
</tr>
<tr>
<td>Disjunction</td>
<td>In compound disjunctive problems probability is often under-estimated</td>
<td>Cohen <em>et al.</em> (1972, p. 42), Bar-Hillel (1973, p. 405) and Noveck <em>et al.</em> (2002, p. 297)</td>
</tr>
<tr>
<td>Egocentric</td>
<td>Occurs when people claim more responsibility for themselves for the results of a joint action than an outside observer would</td>
<td>Ross and Sicoly (1979, p. 322), Bazerman (1998, p. 99) and Leung <em>et al.</em> (2004, p. 406)</td>
</tr>
<tr>
<td>Endowment</td>
<td>The tendency for people to value something higher as soon as they own it</td>
<td>Kahneman <em>et al.</em> (1991, p. 194), Russo <em>et al.</em> (1996, p. 105) and Tom (2004, p. 160)</td>
</tr>
<tr>
<td>Escalation</td>
<td>Often decision makers commit to follow or escalate a previous, unsatisfactory course of action</td>
<td>Staw (1976, p. 27), Northcraft and Wolf (1984, p. 226), Drummond (1994, p. 43, 1995, p. 265) and Bazerman (1998, p. 73)</td>
</tr>
<tr>
<td>Fact-value confusion</td>
<td>Strongly held values may often be regarded and presented as facts</td>
<td>Sage (1981, p. 647) and Mumpower and Stewart (1996, p. 200)</td>
</tr>
<tr>
<td>False consensus</td>
<td>Tendency to think others are just like oneself and to ignore representative information</td>
<td>Sherman (1983, p. 197), Stepman <em>et al.</em> (1999, p. 223) and Thaler (2000, p. 133)</td>
</tr>
<tr>
<td>Familiarity</td>
<td>Decision makers are biased to view more familiar events (and their complements) as more likely than less familiar events</td>
<td>Fox and Levav (2000, p. 269) and Krug and Weaver (2005, p. 437)</td>
</tr>
<tr>
<td>First impression</td>
<td>Decision makers often fail to correct their initial characterizations with additional situational information</td>
<td>McKinney <em>et al.</em> (1987, p. 245), Nordstrom <em>et al.</em> (1998, p. 477) and Rabin and Schrag (1999, p. 37)</td>
</tr>
<tr>
<td>Frequency/redundancy</td>
<td>Repeated statements are given higher validity ratings than non-repeated statements, although this overconfidence is usually unwarranted</td>
<td>Estes (1976, p. 37), Hogarth, 1987, p. 217) and Arkes <em>et al.</em> (1989, p. 81)</td>
</tr>
</tbody>
</table>

*(continued)*
<table>
<thead>
<tr>
<th>Bias/source of bias</th>
<th>Description</th>
<th>Selection of references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Habit</td>
<td>An alternative may be chosen because the decision maker used it before and is used to it</td>
<td>Slovic (1975, p. 283), Sage (1981, p. 648) and Hogarth (1987, p. 219)</td>
</tr>
<tr>
<td>Illusion of control</td>
<td>Perceived good outcome may be based on a poor decision and can induce a false feeling of control over the judgment situation</td>
<td>Langer and Roth (1975, p. 191), Hogarth (1987, p. 221), Gollwitzer and Kinney (1989, p. 531) and Greenberg (1996, p. 165)</td>
</tr>
<tr>
<td>Imaginability</td>
<td>If an event can easily be imagined it may be judged more probable than events which are difficult to image</td>
<td>Tversky and Kahneman (1974, p. 1127), Slovic et al. (1977, p. 4) and Taylor and Thompson (1982, p. 157)</td>
</tr>
<tr>
<td>Impact</td>
<td>Tendency to overestimate the length or the intensity of the impact of future feeling states</td>
<td>Gilbert et al. (1998, p. 617) and Wilson et al. (2000, p. 821)</td>
</tr>
<tr>
<td>Issue valence</td>
<td>Degree to which an issue is positively framed</td>
<td>Mittal et al. (2002, p. 455)</td>
</tr>
<tr>
<td>Law of small numbers</td>
<td>Greater confidence is expressed in predictions based on small samples of data with non-disconfirming evidence than in much larger samples with minor disconfirming evidence</td>
<td>Tversky and Kahneman (1971, p. 105), Hogarth (1987, p. 219) and Rabin (2002, p. 775)</td>
</tr>
<tr>
<td>Loss aversion</td>
<td>The tendency for people to strongly prefer avoiding losses than acquiring gains (value functions that relate subjective to objective losses are steeper than value functions that relate subjective to objective gains)</td>
<td>Kahneman and Tversky (1979, p. 287, 1984, p. 342), Wicker and Hamann (1995, p. 75) and Hastie and Dawes (2001, p. 308)</td>
</tr>
<tr>
<td>Magical thinking</td>
<td>Non-scientific causal reasoning</td>
<td>Shweder (1977, p. 637), Keinan (1994, p. 48) and Bolton et al. (2002, p. 479)</td>
</tr>
<tr>
<td>Mere exposure effect</td>
<td>The mere repeated exposure of the individual to a stimulus is a sufficient condition for the enhancement of his attitude toward it</td>
<td>Zajonc (1968, p. 1), Bornstein (1989, p. 265), Rindfleisch and Inman (1998, p. 8) and Butler and Berry (2004, p. 467)</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Bias/source of bias</th>
<th>Description</th>
<th>Selection of references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-linear extrapolation</td>
<td>Decision makers are often unable to extrapolate a non-linear growth process</td>
<td>Wagenaar and Timmers (1979, p. 240), Hogarth (1987, p. 217) and Mackinnon and Wearing (1991, p. 177)</td>
</tr>
<tr>
<td>Order</td>
<td>The order in which information is presented affects information retention in memory</td>
<td>Hogarth (1987, p. 217) and Chapman et al. (1996, p. 201)</td>
</tr>
<tr>
<td>Overconfidence</td>
<td>People tend to ascribe more credibility to data than is warranted and hence overestimate the probability of success merely due to the presence of an abundance of data – the greater the amount of data, the more confident a person is in the accuracy</td>
<td>Lichtenstein et al. (1982, p. 308), Paese and Feuer (1991, p. 1), Russo and Schoemaker (1992, p. 7), Brenner et al. (1996, p. 212) and Yates and Lee (1996, p. 138)</td>
</tr>
<tr>
<td>Persistence</td>
<td>Persistence in the near term to the alternatives, which have been used before</td>
<td>Boldrin et al. (2001, p. 149) and Kaplan and Schoar (2005, p. 1792)</td>
</tr>
<tr>
<td>Planning fallacy</td>
<td>Tendency to underestimate task-completion times</td>
<td>Buehler et al. (1994, p. 366, 2002, p. 250)</td>
</tr>
<tr>
<td>Primacy effect</td>
<td>The effect refers to the superior recall of information that appears earliest in the presentation of a larger set of information</td>
<td>Bellezza et al. (1982, p. 175), Yates and Curley (1986, p. 293) and Tan and Ward (2000, p. 1589)</td>
</tr>
<tr>
<td>Prior hypothesis bias</td>
<td>Individuals who formed erroneous hypotheses tend to make decisions on the basis of these beliefs despite the presence of abundant evidence that they were wrong</td>
<td>Schwenk (1984, p. 116), Das and Teng (1999, p. 762) and Kahle and White (2004, p. 3)</td>
</tr>
<tr>
<td>Recall</td>
<td>An event may be perceived more probable if its instances are more easily recalled than other equally probable events</td>
<td>Tversky and Kahneman (1973, p. 220), Combs and Slovic (1979, p. 838), Yates (1990, p. 186) and Hastie and Dawes (2001, p. 78)</td>
</tr>
<tr>
<td>Recency effect</td>
<td>The tendency to weigh recent events more than earlier events</td>
<td>Cushing and Ahlawat (1996, p. 110) and Arnold et al. (2000, p. 110)</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Bias/source of bias</th>
<th>Description</th>
<th>Selection of references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference point</td>
<td>The establishment of a reference point, or anchor can be a random act. People like to judge situations starting from a reference point and then adjust judgment.</td>
<td>Kahneman and Tversky (1979, p. 286), Boyle et al. (1998, p. 517), McFadden (1999, p. 85) and Barkan et al. (2005, p. 213)</td>
</tr>
<tr>
<td>Regression</td>
<td>The fact that events will tend to regress toward the mean on subsequent trials is often disregarded in judgments.</td>
<td>Kahneman and Tversky (1973, p. 239), Tversky and Kahneman (1974, p. 1126), Joyce and Biddle (1981b, p. 323) and Hogarth (1987, p. 220)</td>
</tr>
<tr>
<td>Rosy retrospection</td>
<td>Tendency to rate past events more positively than they had actually been rated when they occurred.</td>
<td>Mitchell and Thompson (1994, p. 85) and Golden (1997, p. 1243)</td>
</tr>
<tr>
<td>Scale</td>
<td>Perceived variability of data can be affected by the scale of the data.</td>
<td>Ricketts (1990, p. 64) and Ferreira et al. (1998, p. 183)</td>
</tr>
<tr>
<td>Search</td>
<td>An event may be perceived more probable due to the effectiveness of the search strategy.</td>
<td>Tversky and Kahneman (1974, p. 1127) and Vaughan and Thelwall (2004, p. 694)</td>
</tr>
<tr>
<td>Selectivity</td>
<td>People often seek only information that confirms their views and values.</td>
<td>Anderson (1982, p. 594), Little (1985, p. 1469), Hogarth (1987 p. 216) and Giles (2003, p. 1291)</td>
</tr>
<tr>
<td>Self serving</td>
<td>The tendency to claim more responsibility for successes than failures. Tendency for people to evaluate ambiguous information in a way beneficial to their interests.</td>
<td>Miller and Ross (1975, p. 213) and Babcock and Loewenstein (1997, p. 109)</td>
</tr>
<tr>
<td>Self-fulfilling prophecies</td>
<td>A decision maker values a certain outcome, interpretation, or conclusion and acquires only information that supports this conclusion.</td>
<td>Sage (1981, p. 647), Sorger (1998, p. 363) and Madon et al. (2004, p. 837)</td>
</tr>
<tr>
<td>Series position effect</td>
<td>Items at the beginning of a list are the easiest to recall, followed by the items near the end of a list; items in the middle are the least likely to be remembered.</td>
<td>Frensch (1994, p. 423) and Healy et al. (2000, p. 148)</td>
</tr>
<tr>
<td>Similarity</td>
<td>The likelihood of an event occurring may erroneously be judged by the probabilities of similar events.</td>
<td>Tversky and Kahneman (1973, p. 225) and Hastie and Dawes (2001, p. 111)</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Bias/source of bias</th>
<th>Description</th>
<th>Selection of references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Status quo</td>
<td>Individuals have a strong tendency to remain at the status quo, because the disadvantages of leaving are perceived to be greater than the advantages</td>
<td>Samuelson and Zeckhauser (1988, p. 7), Fernandez and Rodrik (1991, p. 1146) and Kahneman et al. (1991, p. 197)</td>
</tr>
<tr>
<td>Subset</td>
<td>A subset is often judged more probable than its set</td>
<td>Tversky and Kahneman (1983, p. 295), Thuring and Jungermann (1990, p. 51) and Briggs and Krantz (1992, p. 78)</td>
</tr>
<tr>
<td>Success</td>
<td>Often unsatisfactory performance is associated with poor luck or external factors and success with the abilities of the decision maker (fundamental attribution error)</td>
<td>Miller (1976, p. 901), Sage (1981, p. 647) and Hogarth (1987, p. 222)</td>
</tr>
<tr>
<td>Sunk costs fallacy</td>
<td>A maladaptive economic behavior that is manifested in a greater tendency to continue an endeavor once an investment in money, effort or time has been made</td>
<td>Shaanan (1994, p. 717), Sharp and Salter (1997, p. 101), Arkes and Ayton (1999, p. 591) and Hastie and Dawes (2001, p. 36)</td>
</tr>
<tr>
<td>Test</td>
<td>Decision makers tend to attain an unrealistic confidence in judgment when some aspects and outcomes of choice cannot be tested</td>
<td>Birnbaum and Hynan (1986, p. 266) and Terris (1997, p. 28)</td>
</tr>
<tr>
<td>Testimony</td>
<td>Difficulties in recalling details of an event may lead to seemingly logical reconstructions which deviate from reality</td>
<td>Snyder and Uranowitz (1978, p. 942), Wells and Loftus (1984, p. 304) and Ricchiute (1997, p. 28)</td>
</tr>
<tr>
<td>Von Restorff effect</td>
<td>Tendency for an item that stands out like a sore thumb to be more likely to be remembered than other items</td>
<td>Von Restorff (1933, p. 299) and Kelley and Nairne (2001, p. 54)</td>
</tr>
</tbody>
</table>
reliability and validity of the clustering process, the authors employed a qualitative clustering approach modeled after hierarchical clustering (Aldenderfer and Blashfield, 1984), followed by a Q-methodology (Stephenson, 1953).

**Qualitative cluster analysis**
Hierarchical clustering is used to sort objects into like groups (Saunders, 1980). The authors began the qualitative cluster analysis by assuming that each of the 76 biases was a separate cluster (Revelle, 1979). Each decision bias (cluster) was listed on an index card, along with its definition. The two clusters that were viewed as most alike were then combined to form a new composite cluster to give a \(76 - 1 = 75\) cluster solution: one cluster of two decision biases and 74 clusters of individual decision biases. The 75 clusters were then compared to find the next most alike pair, which again was combined to form a new composite cluster. This process continued until all of the original 76 biases were combined into one cluster.

It is important that a researcher avoid inaccurately identifying possible cuts in categorization where the distance between the remaining clusters does not significantly differ (between 76 and 1 in this case) (Saunders, 1980). Thus, the authors analyzed the distances after every step in order to identify a possible cut. Possible cluster solutions were, respectively, evaluated on the visually replicated physical distance and proximity of clusters (Moody et al., 2005), where dissimilarities between biases mentioned on individual cards were expressed by the distance between the two cards on a table, and based on heterogeneity between groups (Pfeifer, 2004). On this basis the authors identified a nine cluster solution as fitting best with the data [1].

Table II provides an overview of these nine categories, which are displayed in alphabetical order. Owing to the subjectivity associated with classification based on hierarchical clustering of qualitative data, a Q-methodology was then conducted to examine the reliability of the nine cluster solution.

**Q-methodology**
A Q-methodology was applied to confirm that the nine cluster solution was mutually exclusive and exhaustive and to assess the reliability and validity of the results of the qualitative cluster analysis. Q-methodology was developed within the field of psychology (Stephenson, 1953) and can be used to examine personal viewpoints, opinions, and attitudes (Martin and Reynolds, 1976). Smith and Smith (1996, p. 3) note that, “Q-methodology for subjectivity adds an objective method of studying self-reference that the interbehavioral field lacks,” thus minimizing effects associated with the possible “idiosyncratic nature of the evaluators” (Davidson and MacGregor, 1996, p. 631) or “the artificial categorizing of statements” (Brown, 1993, p. 97).

Typically, Q-methodology participants are presented with a list of statements about a topic, called the Q-set. These participants, who are referred to as the P-set, are asked to rank the statements or to allocate the statements to a pre-defined set of categories based on their individual judgments. By performing this Q-sort, participants provide their subjective meaning to the statements and thus systematically review their subjective perspectives (Brouwer, 1999). A principal assumption of Q-methodology is that subjectivity can be communicated and expressed in an operant manner, and thus systematically analyzed just as any other behavior (Stephenson, 1993). The Q-methodology also has the advantage of not requiring “large numbers of subjects,”
<table>
<thead>
<tr>
<th>Availability cognition</th>
<th>Availability</th>
<th>Country of origin</th>
<th>Cultural</th>
<th>Familiarity</th>
<th>Home</th>
<th>Imaginability</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base rate</td>
<td>Base rate</td>
<td>Recency effect</td>
<td>Subset</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commitment</td>
<td>Aversion to regret</td>
<td>Concorde fallacy</td>
<td>Endowment</td>
<td>Escalating commitment</td>
<td>Escalation</td>
<td>Loss aversion</td>
<td>Sunk costs fallacy</td>
</tr>
<tr>
<td>Confirmatory</td>
<td>Aversion to ambiguity</td>
<td>Bandwagon effect</td>
<td>Belief</td>
<td>Confirmation</td>
<td>Confirmation evidence</td>
<td>Confirmation</td>
<td>Desire</td>
</tr>
<tr>
<td></td>
<td>Fact-value confusion</td>
<td>Halo effect</td>
<td>Prior hypothesis bias</td>
<td>Selectivity</td>
<td>Self-fulfilling prophecy</td>
<td>Wishful thinking</td>
<td></td>
</tr>
<tr>
<td>Control illusion</td>
<td>Attenuation</td>
<td>Chance</td>
<td>Completeness</td>
<td>Complexity</td>
<td>Conjunction</td>
<td>Control</td>
<td>Correlation</td>
</tr>
<tr>
<td></td>
<td>False consensus</td>
<td>Gambler's fallacy</td>
<td>Hot hand fallacy</td>
<td>Impact</td>
<td>Law of small</td>
<td>Numbers</td>
<td>Magical thinking</td>
</tr>
<tr>
<td></td>
<td>Planning fallacy</td>
<td>(continued)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The P-set generally requires only a limited number of respondents, which depends on the objectives of the analysis (Block, 1961; Brown, 1993, 2004). In this case the primary goal was to measure an interrater reliability of the Q-sample and thus it was necessary to have “two or more researchers” in the P-set (Marques and McCall, 2005, p. 442). The P-set is not random, but rather consists of a structured sample of respondents who are theoretically relevant to the problem under consideration and who are expected to have a clear and distinct viewpoint regarding the phenomenon which is being subjected to the Q-methodology (Brown, 1980). The authors formed a P-set of six participants based on these criteria: three experienced supply management executives and three researchers (none of whom were authors of this paper) in the supply management field who also had prior supply management work experience.

Each decision bias was described by a statement or definition, and was randomly assigned a number. The statements and corresponding numbers were then printed on separate cards – the Q-deck – for Q-sorting. The authors applied a forced Q-sorting
and instructed the P-set participants to allocate each card in the Q-deck to the one cluster from the cluster analysis where the card best fit, where each of the nine clusters were also given definitions. Each participant completed the Q-sorting independently of other participants.

The reliability of the Q-sorting process was calculated based on the percentage of total pairwise agreements between the coders and the results from the cluster analysis. This method of calculating reliability is advantageous as it is easy to understand and minimizes the capitalization on chance agreement between raters given the relatively large number of classification categories (clusters) (Rust and Cooil, 1994). The average inter-rater reliability was the mean of the $76 \times 7$ comparisons (six from the raters and one from the authors’ qualitative cluster analysis) across the six participants, and ranged from 89.5 to 98.7 percent with a mean of 95.0 percent. The intercoder reliability rate can be likened to Cronbach’s (1951) coefficient $\alpha$, given the large number of classification categories (Perreault and Leigh, 1989).

Table III displays a summarizing overview of the discussed decision biases and their effects on judgment and decision rationality, and provides concise examples within supply management contexts. The authors next describe the nine categories of decision biases in greater depth, and include additional supply management examples obtained from the P-set participants.

**Taxonomy of decision biases**

*Availability cognition bias*

The availability cognition bias occurs when a decision maker judges information which is more easily recalled from memory (remembered) as being more probable. Information which is vivid because the decision maker is already familiar with or has prior experience concerning this information is more easily recalled and is evaluated as being more probable than equally probable information with which the decision maker is not familiar (Tversky and Kahneman, 1973; Slovic et al., 1977). There are evolutionary reasons for the availability cognition bias, but in many decision situations it can lead a decision maker to place greater weight on easily remembered information to the detriment of other relevant information (Combs and Slovic, 1979; Hogarth, 1987).

One example of the availability bias is the country of origin effect, where supply managers may choose a supplier from a national culture similar to their own with the erroneous belief that the supplier may produce at a higher level of quality than a supplier from a more disparate national culture. Thus, suppliers representing a national culture that supply managers are unfamiliar with may not be considered or may be erroneously given lower ratings due to this bias (Meernik et al., 2005; Pauleen and Murphy, 2005). As early as, Bruner and Postman (1949) showed that important information is often excluded from decision-making because of the decision maker’s education, affiliation, or profession. An example here would be an engineer who prefers exact specifications and tight tolerance limits versus a supply manager who prefers looser design specifications to avoid difficulties in sourcing, including monopolistic scenarios.

*Base rate bias*

Here, base rate data are ignored or devalued in favor of other, less relevant data (Lyon and Slovic, 1976; Bar-Hillel and Fischhoff, 1981; Bar-Hillel, 1990). This bias often
occurs when base rate data are somewhat abstract in comparison to more concrete, but less relevant additional data. An example of the base rate bias would be deciding to lower safety stock inventory because safety stock has not been needed over the past few inventory cycles, even though demand and leadtime values have not changed and are largely the same within the industry according to benchmarking or related industry association data. The manager in this case may inaccurately perceive risk simply because by chance safety stock was not needed during this time period. As another example, a buyer may ignore historical or industry data concerning a supplier and instead rely more on an anecdote or personal experience of another buyer in judging a supplier. In both cases, the manager would decide to rely on a few or even a single, vivid data point(s), rather than on more reliable but perceptually less lucid data.

The normative approach to combining base rate data with specific or diagnostic data is given by Bayes Theorem. The base rate bias suggests that humans are not

<table>
<thead>
<tr>
<th>Decision bias category</th>
<th>Effect on judgment or decision rationality</th>
<th>Example supply management</th>
</tr>
</thead>
<tbody>
<tr>
<td>Availability cognition</td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>Imaginability or recall of a productive collaboration between producer and supplier may lead to over-optimistic evaluations</td>
</tr>
<tr>
<td></td>
<td>Disregard of relevant alternatives</td>
<td>Adjustment error on reception of new relevant information about supply market development can lead to over-optimistic/-pessimistic evaluations</td>
</tr>
<tr>
<td>Base rate</td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>Imagine the manager would decide to rely on a few or even a single, vivid data point(s), rather than on more reliable but perceptually less lucid data.</td>
</tr>
<tr>
<td></td>
<td>Erroneous evaluation of event probabilities or outcomes</td>
<td>A perceived completeness in presentation of a set of alternative suppliers may lead to an unjustified disregard of other suppliers</td>
</tr>
<tr>
<td>Presentation</td>
<td>Disregard of relevant alternatives</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>Disappointing supplier collaboration may be associated with poor luck and success with the abilities of the supply department</td>
</tr>
<tr>
<td></td>
<td>Erro...</td>
<td>A perceived completeness in presentation of a set of alternative suppliers may lead to an unjustified disreg...</td>
</tr>
<tr>
<td>Control illusion</td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Disregard of alternatives</td>
<td>Disappointing supplier collaboration may be associated with poor luck and success with the abilities of the supply department</td>
</tr>
<tr>
<td>Output evaluation</td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Erro...</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td>Commitment</td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Disregard of relevant alternatives</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td>Confirmatory</td>
<td>Disregard of relevant alternatives</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Erro...</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td>Persistence</td>
<td>Disregard of relevant alternatives</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td>Reference point</td>
<td>Over-optimistic/-pessimistic evaluation</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
<tr>
<td></td>
<td>Erro...</td>
<td>A sequence of random events like previously developed innovations of suppliers can be mistaken for the essential characteristic of a process</td>
</tr>
</tbody>
</table>

| Table III. Summarized overview of decision biases and their effects on rationality | 647 | Behavioral supply management |
intuitively “Bayesian” (Christensen-Szalanski and Beach, 1982; Fischhoff and Beyth-Marom, 1983), and this bias may occur because concrete current information more easily provides access to cognitive scripts than does abstract information or prior statistics (Arrington et al., 1985).

**Commitment bias**

A commitment bias consists of an inappropriate tendency to continue an undertaking once a decision regarding an investment in money, effort, or time has been made, or in other words a tendency to follow or escalate a previous, unsatisfactory course of action. According to microeconomic theory, rational decisions should be based on the assessment of future probabilities. This implies that the past and present are relevant to judgment only to the extent that they provide information that can be used to assess future events. In general, this involves the abandonment of sunk or non-recoverable costs associated with a decision.

Many researchers have shown that once a decision maker commits to a course of action, he or she may consistently adhere to that commitment even if later confronted with facts suggesting that the commitment is a poor choice (Staw, 1976, 1981; Schwenk, 1984; Williams, 1986; Beeler and Hunton, 1997; Arkes and Ayton, 1999). Commitment in these cases can only be rational if the costs of abandonment, or non-commitment, outweigh the benefits (Kahneman et al., 1991; Schwenk, 1986). This latter scenario might arise when the decision maker’s reputation could be seriously damaged and the economic cost of escalation is low. A popular type of commitment bias is the sunk cost fallacy (Shaanan, 1994; Sharp and Salter, 1997). Sunk costs are costs that have already been incurred and which cannot be recovered to any significant degree, such as resources committed to a supplier development effort. When sunk costs influence decisions, the decision maker fails to assess an option based exclusively on its future costs and benefits (Arkes and Ayton, 1999; Hastie and Dawes, 2001).

**Confirmatory bias**

In the case of a confirmatory bias, decision makers seek confirmatory evidence and fail to search for disconfirming information for desired outcomes or strongly held values. Thus, there is a tendency to search for or interpret information in a way that confirms one’s preconceptions. This bias operates against one of the fundamental tenets of the scientific method which is that information that disproves a thesis should be viewed as being more valuable than information that supports a thesis. The failure to regard disconfirming information can thus lead to unjustified confidence in behavior (Fischhoff and Beyth-Marom, 1983; Einhorn and Hogarth, 1986; Russo et al., 1996). Lynn and Williams (1990), for example, showed that decision makers have a tendency to base assessments on personal beliefs, ignoring on-hand probabilities. Managers succumbing to the confirmation bias search for information that confirms their views and values, and systematically ignore disconfirming information (Anderson, 1982; Little, 1985; Hogarth, 1987; Schwenk, 1988; Giles, 2003). Furthermore, these managers tend to believe that sources of “desirable” confirming information are more reliable than sources of disconfirming information (Hogarth, 1987; Babad, 1995; Thaler, 2000; Gordon et al., 2005). For example, a buyer may begin to prefer Supplier A during the selection process due to an encouraging plant visit or a favorable impression of the supplier’s engineering team. When the objective results from a supplier evaluation
matrix indicate that Supplier B should be chosen instead, the buyer may gather additional evidence which supports his preference for Supplier A, while ignoring the disconfirming evidence supporting Supplier B.

**Control illusion bias**

In the case of the control illusion bias, a sequence of random events or non-representative samples can be mistaken as an essential characteristic of a process leading to unrealistic confidence in judgment. This phenomenon can act against the normative principle of statistical independence, which implies that if occurrences are independent, knowledge of one occurrence’s outcome should have no influence on another, ensuing occurrence (Tversky and Kahneman, 1973, 1974; Bar-Hillel, 1982; Hogarth, 1987; Joram and Read, 1996). For example, if “heads” result after each of three coin flips, an individual may assume that there is a high probability of “tails” on the next flip of the coin, when in reality the probability of tails is still 50 percent for the fourth flip of the coin. As another example, a buyer might have experienced strong demands for price increases from suppliers during the last three negotiations when Engineer A was present. Even though Engineer A’s presence had nothing to do with the demands from these suppliers, the buyer might prefer Engineer B over A as a member of future negotiation teams.

The illusion of control can result in several additional biases in decision making. Fischhoff et al. (1978), for example, demonstrated that the perception of a seemingly complete or logical data presentation can stop the search for errors. Consider for example a standardized supplier evaluation system consisting of five dimensions. A buyer may choose a supplier which has received the highest aggregate score across the five dimensions, and she/he may fail to incorporate additional decision criteria relevant to the selection of this particular supplier. There may, for instance, be consolidation in the supplier’s industry where there is a chance that a competitor may purchase the supplier, or where key engineers may leave the supplier’s company. This kind of confidence can seriously reduce decision quality (Fischhoff et al., 1977).

Further, people tend to be overly optimistic due to a false sense of control in evaluating for example compound conjunctive events such as long-term, multi-stage projects (Teigen et al., 1996; Hastie and Dawes, 2001). This is likely one of the major reasons why so many joint development efforts between buyers and suppliers frequently exceed budgets and fail to meet deadlines.

Time pressure, information overload, or other environmental factors can increase the perceived complexity of a task, and may further lead to unjustified simplifications of the decision problem by ignoring or significantly discounting the level of uncertainty (Hogarth, 1987; Maule and Edland, 1997; Ordonez and Benson, 1997; Nordstrom et al., 1998). Compound disjunctive events may also be erroneously judged (Cohen et al., 1972; Langer, 1977; Noveck et al., 2002). Disjunctive events are compound events where components of the compound do not have to be combined to create the final outcome. For example, for a computer to fail only one of a large number of components has to fail. Disjunctive events should be assessed using the addition rule of probability theory (Bar-Hillel, 1973), with expected utility calculated for alternatives and the alternative with the highest expected utility chosen.

Finally, humans are generally poor at perceiving randomness (Peterson et al., 1965; Lichtenstein and Slovic, 1973; Lopes and Oden, 1987; Ayton et al., 1989, 1991).
A sequence of random events or non-representative samples can be mistaken as an essential characteristic of a process, giving a decision maker an unjustified feeling of control which can lead to unrealistic confidence in judgment (Terrell, 1994; Ayton and Fischer, 2004).

**Output evaluation bias**

The output evaluation bias occurs when in retrospect the degree to which an event would have been predicted is usually overestimated, or when failure is associated with poor luck and success with the abilities of the decision maker. The output evaluation bias occurs due to the decision maker’s inability to recall details which led to a certain outcome. This can then lead to an imprecise reconstruction of causal relations between occurrences (Fischhoff and Beyth-Marom, 1975; Buchman, 1985; Mitchell and Thompson, 1994; Golden, 1997). A popular example is the evaluation of the reasons for a success and the reasons for a failure: successful decision outcomes are often interpreted as the result of the person’s decision-making capabilities (Miller, 1976; Sage, 1981; Hogarth, 1987); in contrast, failure is attributed to external factors such as timing, luck, unfair competition, or poor execution by other involved persons (Miller and Ross, 1975; Babcock and Loewenstein, 1997).

The output evaluation bias is related to, but distinct from, the control bias. In the case of a control bias, a buyer sees a logic where there is none, prior to the decision. In the case of an output evaluation bias, the buyer creates a logic in hindsight, that is after the outcome of a decision has become known to the buyer. The control bias addresses situations where poor decision processes have a desirable outcome. The outcome evaluation bias reduces the decision maker’s ability to learn from and exploit the learning potential from past events, and can thus erroneously lead to an increase in a manager’s confidence in his or her decision-making abilities (Connolly and Bukszar, 1990; Mazursky and Ofir, 1997).

**Persistence bias**

With the persistence bias, an alternative is chosen simply because it has been chosen in the past. Here, the decision maker limits the search for new options and does not adequately consider new information (Samuelson and Zeckhauser, 1988; Fernandez and Rodrik, 1991). This represents an extreme instance of bounded rationality. While persistence can be useful in some instances, especially for simple decisions where the results are not important, it can be dysfunctional and counterproductive for important decisions (Slovic, 1975; Sage, 1981; Hogarth, 1987). Individuals have a tendency to remain with the status quo when the decision environment is uncertain (Hammond et al., 1998). A status quo option can further delimit the search for and consideration of new information (Samuelson and Zeckhauser, 1988; Fernandez and Rodrik, 1991). For example, a Chief Purchasing Officer (CPO) may receive positive reports from the manager of his/her company’s international purchasing office in Shanghai, such as savings which averaged 10 percent over the last two years. The CPO may therefore not have searched the job market for a new manager who might have delivered even higher savings.

**Presentation bias**

The presentation bias exists when the mode, mixture, order, or scale within a presentation influences the perceived value of data, thus leading to systematic errors in
judgment. From a normative viewpoint the sequence of presentation of events or information should have no impact on judgment; however, several researchers have shown that this is not the case (McKenney and Keen, 1974; Hogarth, 1987; Vessey, 1994). Managers for example tend to prefer verbal to written reports and within these they prefer face-to-face dialogues to telephone conversations (Bhappu et al., 1997). Furthermore, managers may place greater emphasis on the first or last item of a presentation (Hogarth, 1987; Frensch, 1994; Chapman et al., 1996) or evaluate events differently, depending on whether they are framed as either losses or gains (Kahneman and Tversky, 1979, 1984; Tversky and Kahneman, 1981, 1986). Additionally, the perceived variability of data can be affected by the scale of the data (Ricketts, 1990; Ferreira et al., 1998) or redundant events can be interpreted as being more available leading to overestimating the probability of occurrence or the importance of an event or data (Estes, 1976; Hogarth, 1987; Arkes et al., 1989).

One of the most important effects within the presentation bias is the framing effect. It addresses deviations from the normative rules of cancellation, transitivity, dominance and invariance (Kahneman and Tversky’s, 1979, 1984 and Tversky and Kahneman’s, 1981, 1986 references to rationality assumptions in economics). Such a bias can occur in everyday life from the standpoint of relative versus absolute scales. A 20 percent discount on a $2.00 item may be perceived as significantly greater than the same “40 cents off” promotion.

The most influential explanation of the framing effect is Kahneman and Tversky’s (1979) prospect theory. They showed systematic differences in choices of human beings, when rationally identical choices are differently framed. In their special case people will tend toward risk aversion for gains (i.e. the marginal value received from each additional amount of gain falls dramatically) and risk seeking for losses. As a classic example, a disproportionate percentage of buyers would choose to keep a $10,000 savings as opposed to a 20 percent chance of receiving a $50,000 savings and would prefer a 20 percent chance for a $50,000 price increase over a definite $10,000 price increase, even though the expected value of the savings/gain and the actual savings/gain are equal, as are the actual and expected values of the price increase/loss (Tversky and Kahneman, 1992; Tversky and Fox, 1995).

Reference point bias
The reference point bias occurs when evaluations and adjustments from an initial position or reference point are usually insufficient. Specifically, a decision maker’s judgments of uncertain quantities are biased in the direction of a relevant comparison value or reference point. One of the three common simplifications in human judgment patterns is to begin with an initial position and then to adjust opinions or evaluations (Tversky and Kahneman, 1974). This can be an appropriate strategy in an environment of continuous feedback. In the majority of cases, however, researchers have shown that the amount of adjustment from this initial position is insufficient (Slovic et al., 1977). The results of numerous experiments for example have demonstrated that the final agreement value in negotiations can be biased in the direction of the opening offer (Galinsky and Mussweiler, 2001). This example shows that a reference point can dominate judgment once it has been suggested. It has even been shown that when the anchor is determined randomly and the subjects are aware of the arbitrary nature of its determination, they still fall subject to the reference point bias (Epley and Gilovich, 2005).
For instance, a buyer might demand only incremental improvements in price levels from a supplier, because the current price level “anchors” the buyer’s judgment. In reality, however, the supplier’s price may be far too high. Similarly, target setting for savings potential differentiated for commodity groups is often based on past achievements. Such a procedure can be regarded as rational only if the past achievement is a perfect indicator; however, past achievements often are not the best indication of possible future achievements (Hogarth, 1987).

**Research implications**

The authors are unaware of any other research which has used a scientifically valid set of methodologies to develop a mutually exclusive and exhaustive taxonomy of decision biases. The authors’ research thus makes a contribution by beginning to develop a valid, mutually exclusive, and exhaustive taxonomy of decision biases, based on literature and research streams that are widely dispersed across multiple disciplines, including economics, psychology, and organizational decision-making. Further, the authors introduce the concept of irrationality to the supply chain management field via an extensive literature search and review, and provide specific examples of decision biases within supply management contexts. This is an important contribution to the field, as much of the existing research in the supply management and broader supply chain management fields has assumed rationality on the part of the decision maker via an integration of such theoretical paradigms as neoclassical economics and transaction cost economics. Our hope is that this taxonomy will not only create an awareness of the over-reliance of our field on rational paradigms, but that it will also spur much-needed additional research which recognizes the potential for biases to enter the judgment and decision-making processes of supply managers, as outlined in the next and final section of the paper. Finally, we have followed the call to use more innovative data sources and methodologies (Parente and Gattiker, 2004), which can complement the mail survey methodology which has so dominated our field (Carter and Ellram, 2003). Thus, an additional contribution of our research has been the introduction, description, and use of qualitative cluster analysis and the Q-methodology – research techniques which have been applied scarcely if at all within the supply chain management and supply management fields.

From a managerial standpoint, understanding the nature of decision biases is a first step in the process of deciding how to manage them. Purchasing executives and managers should realize that these biases:

- are cognitive processes to which decision makers are vulnerable when they attempt to cope with uncertainty in decision-making;
- can occur on the side of the buying organization and also on the side of the supplier (e.g. when the supplier uses his/her knowledge about the influence of decision biases on human judgment in a negotiation situation);
- usually have negative consequences on decision-making effectiveness (i.e. incorrect or distorted decisions), and positive effects on decision-making efficiency (i.e. economizing on time and effort in decision making); and
- will in most cases occur because managers unconsciously rely upon them.
As discussed next, one area in need of further research is to gain a better understanding of how and when supply managers should explicitly attempt to mitigate decision biases.

**Future research directions**

In the coming decades acknowledged scholars predict that the study of human cognition will be an important area of research in economics (Thaler, 2000; Frey and Stutzer, 2002; Kahneman, 2003). The study of BSM will also likely become more important in the future due to the uncertainty surrounding even shorter product life cycles, continued shifts in business models, and increased globalization. In addition, the study of human decision making and decision biases have been incorporated in research streams and sub-disciplines of other areas of business research such as finance and management, and have appeared in the top-tier journals of these disciplines (George et al., 2006; Haigh and List, 2005). The results of our research and analysis, together with the empirical results in these other fields of business suggest several avenues for further research in the field of supply management. Specifically, four types of analyses might be considered.

First, the taxonomy of biases introduced in this paper needs further testing. A confirmatory analysis, through the use of a mail survey and confirmatory factor analysis, would extend the external validity of the results of the analyses from our research. The use of such a complementary approach would also allow for triangulation across research methods (McGrath, 1982).

Second, an examination of the moderating effects of decision biases and of debiasing measures in supply management decision situations characterized by various degrees of uncertainty will be cumbersome but fruitful areas of future research. The biases and debiasing measures, such as combining single sourcing items to modules or systems, standardizing sourcing items, and providing various types of training may moderate the relationship between uncertainty constructs on the one hand and the processes and outcomes of supply management decision making on the other hand. Studies that investigate this relationship, both with and without the effects of supply management debiasing (SMD) techniques, should be of keen interest to managers and researchers alike. Decision-making scenarios with high degrees of uncertainty and long-term effects such as early supplier selection or supplier development might be highly suited for such investigations. Another interesting context would be decisions involving highly complex and dynamic markets such as those in rapidly developing economies.

Third, analyzing how supply managers make the trade off between higher degrees of rationality and economizing on their time and effort when making certain supply decisions will help executives to determine when buyers should be required to explicitly use certain SMD techniques. Such studies will also shed light on another largely neglected research area, namely to what degree supply managers engage in “satisficing” as opposed to “optimizing” in their search for more information in uncertain situations.

Fourth, it might be interesting to see to what extent decision biases and SMD techniques have different effects in different cultures. Hofstede (2001) has shown that uncertainty avoidance is one of the five major dimensions of national culture. How might differences across national cultures affect the decision-making process of buyers in decentralized and geographically dispersed buying organizations? The same
reasoning and research question might apply to different corporate cultures and to personality types of supply managers.

The objective of our research was to introduce BSM to the field of supply management through a review of the extant research, and to provide a parsimonious means by which both managers and researchers might better understand these biases. In so doing, our goal was also to create an awareness among researchers of the need to extend the assumptions of homo economicus, a key tenet of the economic theory in which a relatively large portion of the supply management literature is grounded. Our hope is that our literature review, analyses, and results will stimulate much needed additional supply management research in this area.

Note 1. The nine cluster solution fit with our classification criteria of achieving internal consistency while not confusing different levels of abstraction within the classification. In order to move from the nine to the eight cluster solution, two of the nine clusters would have to be merged, leading to a violation of the criteria.

References


Further reading


About the authors

Craig R. Carter is an Associate Professor of Supply Chain Management at the University of Nevada. His primary research stream focuses on the socially responsible management of the
supply chain. This research stream encompasses ethical issues in buyer-supplier relationships, environmental supply management, diversity sourcing, perceptions of opportunism surrounding electronic reverse auctions, and the broader, integrative concepts of social responsibility and sustainability. A secondary and often intersecting area of research examines international and cross-cultural supply chain management issues. He is a member of the editorial review boards of several journals, and the Co-Editor of the *Journal of Supply Chain Management*. His research has appeared in numerous supply chain management journals including *Decision Sciences, International Journal of Physical Distribution & Logistics Management, Journal of Business Logistics, Journal of Operations Management, Journal of Supply Chain Management, Transportation Journal*, and *Transportation Research E*. E-mail: crcarter@unr.edu

Lutz Kaufmann is a Professor and The Herbert Quandt Endowed Chair in International Business and Supply Management at WHU – Otto Beisheim School of Management in Vallendar, Germany. He also serves as the Director of WHU’s Asia Center and its Executive Development Programs. His research focuses on international strategy and supply management. He is a member of the editorial review boards of several journals, and the Co-Editor of the *Journal of Supply Chain Management*. His work appeared in the *Journal of Operations Management, Journal of World Business, Journal of International Marketing, Journal of Supply Chain Management, Transportation Research E*, and *The Journal of Purchasing & Supply Management*. He has published more than a dozen books on strategy and supply management. Lutz Kaufmann is the corresponding author and can be contacted at: lutz.kaufmann@whu.edu

Alex Michel is a research associate at WHU – Otto Beisheim School of Management in Vallendar, Germany. His primary research stream focuses on supply management decision making. E-mail: alex.michel@whu.edu

To purchase reprints of this article please e-mail: reprints@emeraldinsight.com
Or visit our web site for further details: www.emeraldinsight.com/reprints