

THE CAPCO INSTITUTE
JOURNAL
OF FINANCIAL TRANSFORMATION

OPERATIONS

Decision-making under pressure
(a behavioral science perspective)

FLORIAN KLAPPROTH

20
YEAR ANNIVERSARY

**OPERATIONAL
RESILIENCE**

#53 MAY 2021

THE CAPCO INSTITUTE

JOURNAL OF FINANCIAL TRANSFORMATION

RECIPIENT OF THE APEX AWARD FOR PUBLICATION EXCELLENCE

Editor

Shahin Shojai, Global Head, Capco Institute

Advisory Board

Michael Ethelston, Partner, Capco

Michael Pugliese, Partner, Capco

Bodo Schaefer, Partner, Capco

Editorial Board

Franklin Allen, Professor of Finance and Economics and Executive Director of the Brevan Howard Centre, Imperial College London and Professor Emeritus of Finance and Economics, the Wharton School, University of Pennsylvania

Philippe d'Arvisenet, Advisor and former Group Chief Economist, BNP Paribas

Rudi Bogni, former Chief Executive Officer, UBS Private Banking

Bruno Bonati, Former Chairman of the Non-Executive Board, Zuger Kantonalbank, and President, Landis & Gyr Foundation

Dan Breznitz, Munk Chair of Innovation Studies, University of Toronto

Urs Birchler, Professor Emeritus of Banking, University of Zurich

Géry Daeninck, former CEO, Robeco

Jean Dermine, Professor of Banking and Finance, INSEAD

Douglas W. Diamond, Merton H. Miller Distinguished Service Professor of Finance, University of Chicago

Elroy Dimson, Emeritus Professor of Finance, London Business School

Nicholas Economides, Professor of Economics, New York University

Michael Enthoven, Chairman, NL Financial Investments

José Luis Escrivá, President, The Independent Authority for Fiscal Responsibility (AIReF), Spain

George Feiger, Pro-Vice-Chancellor and Executive Dean, Aston Business School

Gregorio de Felice, Head of Research and Chief Economist, Intesa Sanpaolo

Allen Ferrell, Greenfield Professor of Securities Law, Harvard Law School

Peter Gomber, Full Professor, Chair of e-Finance, Goethe University Frankfurt

Wilfried Hauck, Managing Director, Statera Financial Management GmbH

Pierre Hillion, The de Picciotto Professor of Alternative Investments, INSEAD

Andrei A. Kirilenko, Reader in Finance, Cambridge Judge Business School, University of Cambridge

Mitchel Lenson, Former Group Chief Information Officer, Deutsche Bank

David T. Llewellyn, Professor Emeritus of Money and Banking, Loughborough University

Donald A. Marchand, Professor Emeritus of Strategy and Information Management, IMD

Colin Mayer, Peter Moores Professor of Management Studies, Oxford University

Pierpaolo Montana, Group Chief Risk Officer, Mediobanca

John Taysom, Visiting Professor of Computer Science, UCL

D. Sykes Wilford, W. Frank Hipp Distinguished Chair in Business, The Citadel

CONTENTS

OPERATIONS

08 Collaborating for the greater good: Enhancing operational resilience within the Canadian financial sector

Filipe Dinis, Chief Operating Officer, Bank of Canada

Contributor: **Inderpal Bal**, Special Assistant to the Chief Operating Officer, Bank of Canada

14 Preparing for critical disruption: A perspective on operational resilience

Sanjiv Talwar, Assistant Superintendent, Risk Support Sector, Office of the Superintendent of Financial Institutions (OSFI)

18 Operational resilience: Industry benchmarking

Matt Paisley, Principal Consultant, Capco

Will Packard, Managing Principal, Capco

Samer Baghdadi, Principal Consultant, Capco

Chris Rhodes, Consultant, Capco

24 Decision-making under pressure (a behavioral science perspective)

Florian Klapproth, Professorship of Educational Psychology, Medical School Berlin

32 Operational resilience and stress testing: Hit or myth?

Gianluca Pescaroli, Lecturer in Business Continuity and Organisational Resilience, and Director of the MSc in Risk, Disaster and Resilience, University College London

Chris Needham-Bennett, Managing Director, Needhams 1834 Ltd.

44 Operational resilience approach

Michelle Leon, Managing Principal, Capco

Carl Repoli, Managing Principal, Capco

54 Resilient decision-making

Mark Schofield, Founder and Managing Director, MindAlpha

64 Sailing on a sea of uncertainty: Reflections on operational resilience in the 21st century

Simon Ashby, Professor of Financial Services, Vlerick Business School

70 Operational resilience

Hannah McAslan, Senior Associate, Norton Rose Fulbright LLP

Alice Routh, Associate, Norton Rose Fulbright LLP

Hannah Meakin, Partner, Norton Rose Fulbright LLP

James Russell, Partner, Norton Rose Fulbright LLP

TECHNOLOGY

80 Why cyber resilience must be a top-level leadership strategy

Steve Hill, Managing Director, Global Head of Operational Resilience, Credit Suisse, and Visiting Senior Research Fellow, King's College, London

Sadie Creese, Professor of Cybersecurity, Department of Computer Science, University of Oxford

84 Data-driven operational resilience

Thadi Murali, Managing Principal, Capco

Rebecca Smith, Principal Consultant, Capco

Sandeep Vishnu, Partner, Capco

94 The ties that bind: A framework for assessing the linkage between cyber risks and financial stability

Jason Healey, Senior Research Scholar, School of International and Public Affairs, Columbia University, and Non-Resident Senior Fellow, Cyber Statecraft Initiative, Atlantic Council

Patricia Mosser, Senior Research Scholar and Director of the MPA in Economic Policy Management, School of International and Public Affairs, Columbia University

Katheryn Rosen, Global Head, Technology and Cybersecurity Supervision, Policy and Partnerships, JPMorgan Chase

Alexander Wortman, Senior Consultant, Cyber Security Services Practice, KPMG

108 Operational resilience in the financial sector: Evolution and opportunity

Aengus Hallinan, Chief Technology Risk Officer, BNY Mellon

116 COVID-19 shines a spotlight on the reliability of the financial market plumbing

Umar Faruqui, Member of Secretariat, Committee on Payments and Market Infrastructures, Bank for International Settlements (BIS)

Jenny Hancock, Member of Secretariat, Committee on Payments and Market Infrastructures, Bank for International Settlements (BIS)

124 Robotic process automation: A digital element of operational resilience

Yan Gindin, Principal Consultant, Capco

Michael Martinen, Managing Principal, Capco

MILITARY

134 Operational resilience: Applying the lessons of war

Gerhard Wheeler, Head of Reserves, Universal Defence and Security Solutions

140 Operational resilience: Lessons learned from military history

Eduardo Jany, Colonel (Ret.), United States Marine Corps

146 Operational resilience in the business-battle space

Ron Matthews, Professor of Defense Economics, Cranfield University at the UK Defence Academy

Irfan Ansari, Lecturer of Defence Finance, Cranfield University at the UK Defence Academy

Bryan Watters, Associate Professor of Defense Leadership and Management, Cranfield University at the UK Defence Academy

158 Getting the mix right: A look at the issues around outsourcing and operational resilience

Will Packard, Managing Principal, and Head of Operational Resilience, Capco



DEAR READER,

Welcome to this landmark 20th anniversary edition of the Capco Institute Journal of Financial Transformation.

Launched in 2001, the Journal has followed and supported the transformative journey of the financial services industry over the first 20 years of this millennium – years that have seen significant and progressive shifts in the global economy, ecosystem, consumer behavior and society as a whole.

True to its mission of advancing the field of applied finance, the Journal has featured papers from over 25 Nobel Laureates and over 500 senior financial executives, regulators and distinguished academics, providing insight and thought leadership around a wealth of topics affecting financial services organizations.

I am hugely proud to celebrate this 20th anniversary with the 53rd edition of this Journal, focused on 'Operational Resilience'.

There has never been a more relevant time to focus on the theme of resilience which has become an organizational and regulatory priority. No organization has been left untouched by the events of the past couple of years including the global pandemic. We have seen that operational resilience needs to consider issues far beyond traditional business continuity planning and disaster recovery.

Also, the increasing pace of digitalization, the complexity and interconnectedness of the financial services industry, and the sophistication of cybercrime have made operational disruption more likely and the potential consequences more severe.

The papers in this edition highlight the importance of this topic and include lessons from the military, as well as technology perspectives. As ever, you can expect the highest caliber of research and practical guidance from our distinguished contributors. I hope that these contributions will catalyze your own thinking around how to build the resilience needed to operate in these challenging and disruptive times.

Thank you to all our contributors, in this edition and over the past 20 years, and thank you, our readership, for your continued support!

A handwritten signature in black ink, appearing to read 'Lance Levy', with a stylized, flowing script.

Lance Levy, **Capco CEO**

DECISION-MAKING UNDER PRESSURE (A BEHAVIORAL SCIENCE PERSPECTIVE)

FLORIAN KLAPPROTH | Professorship of Educational Psychology, Medical School Berlin

ABSTRACT

Making decisions is critical to the success of any business or field, however, the right decision is often hard to reach and decision-makers frequently do not behave as normative models on decision-making prescribe. Deviations from predictions based on normative decision-making models often occur when decision-makers are under some form of pressure, be it information overload, limited time, or uncertainty. This article illustrates what decisions are, how they are made, how decision-makers arrive at sound decisions when under pressure, and how they are affected by external pressure.

1. INTRODUCTION

Decisions arise from the need to solve a problem or the need for change. Gathering the right amount of information and input from stakeholders is essential for making informed decisions. Rational decision-making is regarded as a primary function of management. Decisions, therefore, play an important role as they determine both organizational and managerial activities.

The decision-making process involves determining a goal, collecting relevant and necessary information, and weighing the alternatives in order to make an appropriate decision. The concept sounds simple, but many people overlook some of the critical stages and risks that occur when making decisions. Wherever possible, it is important to make the best decisions under the circumstances.

Circumstances might not always be easy because decisions must often be made under conditions that are stressful. Managers and other professional decision-makers frequently identify time pressure as a major constraint on their behavior.

Despite the intention to make rational decisions, the executives who make them are impacted by stress just like everyone else and are equally prone to making inappropriate decisions when under pressure. Moreover, the types of decisions that executives must make are particularly vulnerable to the effects of stress because they frequently involve complex and difficult issues.

This article illustrates what decisions are, how they are made, how they are affected by external pressure, and how decision-makers arrive at sound decisions, albeit under pressure.

2. WHAT ARE DECISIONS (AND WHAT DISTINGUISHES THEM FROM JUDGMENTS)?

Although the terms “decision” and “judgment” mean similar things and are sometimes used interchangeably, historical analysis of their use shows that there are some differences regarding both concepts. Let us start with a simple distinction. Decisions are choices. A decision-maker is someone who has to select one of several options in order to get the “best” of the options. Judgments, however, are not necessarily concerned with choices but are integrations of different cues (or pieces of information) that consolidate the understanding of a situation. The following example illustrates the differences and the similarities between decisions and judgments. Suppose a clinical psychologist wants to apply the most appropriate treatment to a client. To reach this goal, the psychologist has to judge the client, that is, to examine the client’s problems, clinical symptoms, personal context, history of diseases, etc. The information obtained by questioning and testing the client will determine the psychologist’s judgment. This judgment is called the diagnosis, which forms the basis for introducing a treatment plan. Yet, it may not always be accurate because some cues obtained from the client may also be indicative

of a different diagnosis. Based on the information collected though, the psychologist nonetheless has to choose the most credible option of all.

The example shows that judgment and decision-making are close to one another but different. Researchers from various disciplines have treated both as completely different concepts for decades and consequently developed different theories to explain how judgments and decisions are generated by humans. Early psychological research on judgment was primarily focused on how humans integrate different cues into a single judgment. This research was influenced by Brunswik (1952), who posited that judgment is similar to perception. Like perception, a judgment is derived from ambiguous cues presented in a given situation, and the person judging has to infer a single estimate based on them. In contrast to perceptual approaches to judgment, early research on decisions has been driven by economics, where the concept of expected utility emerged [e.g., von Neumann and Morgenstern (1944)]. This means that choices can be modeled as always favoring the alternative with the highest expected utility. With the aim of maximizing utility, decision-making has an aura of being rational.

2.1 How are decisions made?

Mathematicians were among the first researchers interested in human decision-making. Bernoulli, a Swiss mathematician and physicist, provided the basis for the so-called “expected utility theory” (EUT) in the 18th century, which was later developed by von Neumann and Morgenstern (1944). Expected utility theory has been used to explain various phenomena, such as insurance purchases or the relation between spending and saving. It serves as a normative theory, according to which optimal decisions can be reached. It has the following core assumptions: (1) every option has a value independent of the value of other options, (2) the value of an option is calculated by using all available information, and (3) in order to calculate the value of an option, low values on one attribute can be compensated for by high values on another attribute. For example, if an individual chooses between different smartphones varying on a number of attributes (price, storage size, color, etc.), they would consider each smartphone independently, (2) use all the available attributes, and (3) calculate the sum of the values for each attribute.

The early economic view on decision-making rests on the assumption that decisions ought to be rational. They are rational if they lead to actions that are well adapted to their goals. That is, if a decision results in an action that allows for reaching a prespecified goal, then the decision is rational.

According to this view, an individual chooses from a collection of options one that has maximum utility. However, the criteria of utility are often vague and often measured by monetary profit [Simon (1993)]. Moreover, even if we assume that human beings are able to use the criterion of utility to make a rational decision, it is unclear where the alternatives of choice come from and whether the collection of options actually represents the complexity of the world. Are human beings really capable of seeing all the possible solutions to a given problem? This is where psychology comes into play.

In fact, there is ample evidence that individuals do not generally behave according to the expected utility theory or other normative decision models. People rarely evaluate options separately but rather relative to other options. Their preferences will, therefore, vary when presented with different alternative options. Imagine an electronics store that has a one-day clearance sale and is offering two electronic devices well below the list price [Shafir et al. (1993)]. Suppose that you have to choose between three options: (1) buying a popular medium-priced electronic device, (2) buying an electronic device that is qualitatively better but more expensive, or (3) waiting to learn more about both devices on sale. In this scenario, most people prefer the waiting option because they just do not know which device they are better off with. When, however, the choice is only between the cheaper device and waiting to learn more about the other devices (i.e., the more expensive device is not on sale), most people prefer the cheaper device because there is no alternative device on offer, and it seems wise not to delay the purchase. Furthermore, people do not search exhaustively for information before making a decision. On the contrary, they employ a limited search, sometimes terminating their search even after having considered only one attribute [Bröder (2000)]. Finally, decision-makers frequently do not add up all attributes’ values. Instead, decisions are made on dominant salient attributes. For example, Gilbride and Allenby (2004) found that when participants chose between cameras varying on seven different attributes, the majority of participants based their decision on only one attribute (e.g., price).

3. PRESSURE LETS DECISIONS DEVIATE FROM OUTCOMES PREDICTED BY NORMATIVE MODELS

Deviations from predictions of normative decision-making models like expected utility theory often occur when decision-makers are under some form of pressure. Compared to low-pressured individuals, pressured decision-makers often have impaired performances [Ahituv et al. (1998)], make

more cognitive errors [Baradell and Klein (1993)], use more stereotypes [Gilbert and Hixon (1991)], demonstrate a greater tendency to ignore situational contexts [Endsley (1995)], and revert to familiar responses based on prior experiences, even if they are inadequate [Kaemph et al. (1996)].

3.1 Types of pressure in decision-making

Types of pressure in decision-making are specific and inherent to the decision environment and, unlike job stressors, they do not last beyond the task at hand. Psychologists have developed theories that might account for effects of pressure on decisions. For example, the “cognitive resource theory” [Fiedler and Garcia (1987)] explains how pressure can negatively impact cognitive processing and decision quality. Harmful effects of pressure on decision quality occur as cognitive resources are diverted to managing stress, such that information processing will be distorted [Vecchio (1990)]. Another psychological theory is the “decision conflict theory” [Janis and Mann (1977)]. It suggests that decision-makers cope with stress by becoming hyper-vigilant in their search for information. In this emotional state, they may frantically search for a solution, fail to consider all alternatives, process information in a disorganized manner, and rapidly shift between possible solutions.

So, what makes decision-making stressful? In the literature, some factors have repeatedly and consistently been shown to be experienced as pressure for decisions-makers, namely information overload, time pressure, and uncertainty.

3.1.1 INFORMATION OVERLOAD

Whereas it seems reasonable to assume that decision-makers should process as much information as possible, the “theory of bounded rationality” [Simon (1957)] postulates that humans only have limited capacity to process complex problems and information. Up to a certain point, decision-making performance is positively correlated with the amount of information available to the decision-maker. Beyond that, the information processing requirements of a task exceed the information-processing capacities, resulting in a state of information overload [Bright et al. (2015)]. The load of information in decision-making has often been defined as the number of information cues available to the decision-maker. In addition, information load may increase with task complexity.

Since decision-makers have limited cognitive processing capacity, information overload is likely to impair decision quality [Chewning and Harrell (1990)] and an increase in time is likely required to make a decision [Cohen (1980)].

Time appears critical to the concept of information overload. With sufficient time, decision-makers potentially process all the available information. Consequently, information overload often occurs when the time required to meet the processing requirements exceeds the amount of time available.

3.1.2 TIME PRESSURE

In many real-life situations, shortage of time or the existence of an external deadline is a natural characteristic of the decision environment. Time pressure occurs when the environment sets a time limit to complete a task that results in feelings of stress and coping with the constraint [Ordonez and Benson (1997)].

Time pressure is common in many settings, particularly in fields where important and complex decisions must be made (e.g., aviation, medical, public administration, chemical and nuclear plant control rooms in cases of crises, etc.). In high-tempo event-driven environments, individuals may have neither the time nor the cognitive resources required to examine and evaluate multiple options [Maule (1997)].

Staw et al. (1981) posited that decision-makers under time pressure have a tendency to show more rigid behavior, described as the failure to alter and adapt behavior to a new situation. Less information is processed because there is a narrowing of the field of attention and a simplification of information processing. This manifests itself as a tendency toward dominant, well-learned, and habitual behavior, regardless of the circumstances of a specific situation.

Imposing a deadline is the common way of generating time pressure. This usually results in people asking, “How much time is left?”, suggesting that attention be divided between the passage of time and the decision process. Thus, some researchers [e.g., Zakay (1993)] propose that when decision-makers are aware of the time limit within which they must reach a decision, they automatically divide their attention between executing two simultaneous cognitive tasks: decision-making and time estimation. The more resources are allocated to the time estimation process, the fewer resources are left to the decision process. Correspondingly, information processing efficiency and response caution in decision-making correlate with timing ability. This suggests that good timers might also be efficient in processing the relevant information to reach decisions under temporal constraints.

The presence of deadlines may induce a number of different emotional states [Maule et al. (2000)]. A positive state may occur when individuals estimate that they can reach task goals

by adapting their cognitive strategy, whereas a negative state likely occurs when they think that they cannot, particularly if the decision is critical. Temporal pressure may also be perceived positively, like in games and sports where the challenge of acting within a limited time period is what makes the activity enjoyable [Freedman and Edwards (1988)].

However, a decision that takes longer to make is not necessarily better. Eisenhardt (1989) found that quick decisions made by top management teams were of higher quality than those that took longer. In her study, fast decisions took between 1.5 and 4 months and longer ones lasted between 12 and 18 months. The fast decisions reflected more frequent meetings within the company, more real-time information being available, more experienced advisors, and more integration in dealing with disagreements and conflicts.

Time pressure may enhance effort and lead to faster processing of information [Maule et al. (2000)]. Moreover, the application of simplified and even more effective strategies might be encouraged because people do not have the time to finish slow analytical decision-making [Harreveld et al. (2007)].

3.1.3 UNCERTAINTY

Decisions can be differentiated by their relative degree of uncertainty because some decision situations offer more information about the expected outcomes than others. According to Weber and Johnson (2009), each decision can be placed on a continuum going from being uncertain to risky to certain. In an uncertain decision, the outcomes and their corresponding probabilities are unknown (like future outcomes of a stock). With a risky decision, the possible outcomes and their probabilities are known (like with tossing a coin). In certain decisions, all possible outcomes are known and their occurrence is deterministic (like in a mathematical equation).

Generally, it can be said that decision-makers attempt to avoid taking risks. Individuals usually do not opt for the highest value but for the safest one. In other words, people are risk averse. If possible, a sure gain is preferred over a gamble [Tversky (1975)].

In economics, risk aversion and a high degree of uncertainty of decision outcomes have been shown to correlate with a lower level of investment decisions [Sauner-Leroy (2004)]. Risk-averse decisions are supposed to outweigh the probability of losses resulting from choices with unpredictable outcomes [Schneider and Lopez (1986)]. Moreover, the likelihood

to engage in risky decisions depends on the degree of uncertainty of outcome predictability [Ellsberg (1961)] and the framing of a decision as a potential gain or loss [Buckert et al. (2014), Kahneman and Tversky (1984)].

4. DECISION-MAKERS ARE SATISFICERS RATHER THAN OPTIMIZERS

Research has demonstrated that humans do not always make strategic, well thought out decisions. Instead, they have been shown to make decisions based on heuristics and other “non-rational” or intuitive tendencies [Gigerenzer and Todd (1999)]. Non-rationality in decision-making is captured by the concept of bounded rationality, a term invented by Nobel Prize winner Herbert Simon. He observed that under the constraints and pressure of much of everyday life, people are incapable of making decisions according to normative decision models.

Two ideas are the centerpiece of Simon's original conceptualization of bounded rationality [Simon (1979)]. The first is “satisficing”. Simon observed that humans do not optimize but instead tend to select the first decision option that exceeds a specified aspiration level, without considering all possible options. He questioned the idea that generating all possible alternatives is even possible, since limits on human calculation capacity prohibit always finding the best alternative. The second idea is the notion that what is or is not rational is not only a characteristic of the decision-maker but also depends on the environment. There may be environments where mere guessing is a rational decision strategy (for instance, in a casino), whereas in other environments guessing would very likely result in faulty decisions (like in mate selection).

According to the theory on human bounded rationality, it appears useful or even necessary for decision-makers to use simplified decision-making heuristics in order to deal with complex and uncertain environments.

4.1 How do people deal with pressure when making decisions?

The three aforementioned kinds of pressure in decision-making – information overload, uncertainty, and limited time – make replacement of complex decision strategies by applying decision heuristics even more relevant. When the amount or complexity of information available to a decision-maker exceeds their cognitive capacity, less effortful decision strategies might be favorable. When time is limited, such that

the decision-making process takes more time than available, less time-consuming decision strategies might be required. When a decision has to be made in an uncertain environment, decision quality potentially improves if strategies are applied that cope with uncertainty.

Heuristic strategies are structurally simple and reliable when optimization algorithms lose feasibility. Examples of optimization strategies are regression analyses and cluster analyses. With regression analyses, an outcome is predicted by the additive combination of predictor variables, each of which is given a certain value or weight. The weights are derived from an algorithm that minimizes the squared differences between predicted and actual outcomes. Cluster analyses put things or people together according to prespecified attributes and maximum similarity.

Let us consider the following example. Suppose that a company wants to predict whether a customer will use their service. This is a typical regression problem, which can be solved by determining variables (predictors) that are supposed to correlate with the usage of the service. If age, gender, and whether or not customers have used the service before are the variables, a simple regression equation would relate the probability of using or not using the service to the weighted sum of the predictors. Now suppose that the company wants to decide which services should be recommended to which people. This is a decision problem that can be solved by clustering. There are complex algorithms to help identify customers that are similar to others on the basis of various characteristics. Groups of people are identified based upon their similarities.

In contrast to these complex math-intensive algorithms, heuristics are more like a rule of thumb and people use them either consciously or unconsciously. When unconsciously used, decisions are often taken from people's gut feelings or intuition [Gigerenzer (2007)].

Popular (and well researched) heuristics are "tallying" and "take-the-best" [Todd and Gigerenzer (2000)]. A decision is reached with tallying by counting the number of cues favoring one alternative over another. For example, when a teacher wants to decide whether a student should repeat a school year or pass to the next grade, they would merely count the cues that favor passing and those that favor being left back (e.g., grades, learning motivation, social behavior, willingness to cooperate, etc.). The option with the highest number gets selected. Take-the-best, however, implies that cues are rank-ordered according to their predictive validity

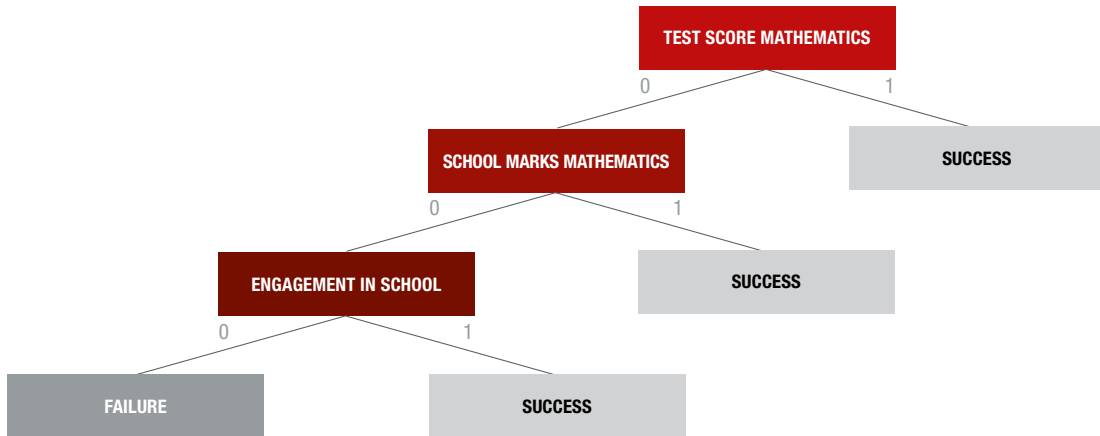
in determining the criterion (grades are most predictive for school success). The take-the-best heuristic means that a sequential search is conducted through the cues, beginning with the most predictive one. The option then taken is that favored by the highest ranked cue. To illustrate, when grades are most predictive (followed by learning motivation and social behavior) they are most crucial, so high grades result in a decision for promotion and low grades lead to grade retention. No other cue would be considered. However, if grades are not decisive (i.e., not favoring either option), the second-highest ranked cue is considered, resulting in either a decision for promotion (in case of high motivation) or retention (in case of low motivation). If the second-highest ranked cue does not permit a decision, the next cue is considered, and so forth.

Heuristics have been described as efficient cognitive processes that ignore part of the information, using a minimum of time, knowledge, and computation to make decisions in real environments [Todd and Gigerenzer (2000)]. This characterization of heuristics differs from earlier accounts that see heuristics as imperfect approximations of rational decision procedures [Tversky and Kahneman (1974)]. Research has shown that the opposite is true. Heuristic strategies are often more effective and lead to more accurate decisions than optimization algorithms, such as the recognition heuristic.

In an experiment conducted by Goldstein and Gigerenzer (2002), German and American students were presented with pairs of U.S. cities and asked to make a decision about which city is larger. When presented with Detroit and Milwaukee, 90 percent of the German students chose the correct answer (Detroit) while only 60 percent of the Americans answered correctly. Goldstein and Gigerenzer (2002) attributed the higher accuracy of German students to their use of the recognition heuristic, according to which a choice is made by what is most recognized. Because most of the German students had never heard of Milwaukee, they chose Detroit as opposed to the American students who could not use the heuristic effectively since they knew both cities.

This experiment demonstrates that a good heuristic can be superior to a complex decision strategy. The recognition strategy works if there is a correlation between the recognition of an option and the judgment criteria, which in this example is between the level of familiarity and the size of a city.

Heuristics especially work well if there is uncertainty in the environment. Rational decision theories require perfect knowledge about relevant cues and their probabilities. But the real world is different. Relevant information is often unknown or

Figure 1: A take-the-best decision tree for the identification of students at risk of school failure

Adapted from Klapproth and Schaltz (2013)

has to be estimated from small samples, so that the conditions for rational decision theories are rarely met. Simple heuristics are actually even more accurate than statistical methods that use the same or more information. In an early study, Dawes and Corrigan (1974) showed that simple linear regression models with equal weights predicted outcomes with the same, and sometimes even more, precision than complex regression models with optimized weights.

The take-the-best heuristic is another example of heuristics that is feasibly superior to regression models. Although complex algorithms can mimic outcomes of the take-the-best heuristic and are, therefore, able to fit existing data, they are inferior to this heuristic when unknown data has to be predicted. The take-the-best heuristic can be depicted as a simple decision tree (also called a fast-and-frugal decision tree).

Klapproth and Schaltz (2013) developed a fast-and-frugal decision tree consisting of maximal three attributes. Students at risk of school failure were more often correctly identified when simple take-the-best decision trees were used, compared to when regression models with 10 predictor variables were applied. Notably, even a decision tree with only one (!) attribute outperformed the regression model. Figure 1 illustrates the decision tree used by Klapproth and Schaltz (2013), whereby three attributes predict whether a student will fail or succeed in school.

4.2 The difference between “clinical” and “mechanical” decision-making

In decision-making, it is important to not only use the correct information but also to combine information in an optimal way. There are two ways of combining data to reach a decision: “clinical” versus “mechanical” [Grove and Meehl (1996), Meehl (1954)]. The so-called clinical method (sometimes called the holistic method) relies on informal contemplation. When applying the clinical method, decision-makers put data together using informal subjective methods. Some clinical decisions are based on “gut feelings”, but they are not restricted to them. Decision-makers can often explain the reason for their decisions, but in clinical decision-making the reasons are “in the mind”. Consequently, because the decision-making process is not transparent to others and, therefore, not reproducible, there are usually large differences in how decisions are reached by different decision-makers.

In contrast, the mechanical method (sometimes called the statistical or actuarial method) involves formal, algorithmic, and objective procedures (e.g., rules, decision trees, equations) for making a decision. It is well specified and does not differ between decision-makers; hence it is perfectly reproducible and could even be performed by machines (computers, robots). The difference between clinical and mechanical decisions is predominantly about the combination of information. If the combination of information is based on a specified rule, the decision-making is mechanical. If the combination of information is based on intuition or personal experience, the occurring decision-making is clinical.

Two examples should illustrate the difference between both methods. In an early study by Yu et al. (1979), medical decisions on whether patients should be covered by therapy or not were made by both human physicians (specialized in that discipline) and a computer program. The same information input was presented to both. Independent evaluators rated the diagnostic decisions of both the computer and the physicians. The result was that while 65 percent of the computer decisions were rated as acceptable, only 56 percent of those made by physicians were rated acceptable.

Another example is the judgment of a newborn. If a doctor judges the physical state of a newborn by intuition and experience, it is a clinical judgment. On the contrary, if the doctor applies the Apgar score, in which a newborn gets a score on five dimensions (heart rate, respiration, reflex, muscle tone, and color), it would be a mechanical decision rule.

There are robust empirical research findings on the subject of making decisions that show that it is better to combine information according to a decision rule than to combine data intuitively [Kuncel et al. (2013)]. Additionally, the average superiority of mechanical over clinical decisions has been exhibited in a number of different fields, such as medicine, education, psychology, and finance. The reason for the advantage of mechanical procedures lies in human proneness to making errors. Typical errors committed in decision-making are due to the ignorance of base rates, the assignment of nonoptimal weights to cues, and the failure to properly assess covariation between variables.

Even educational decisions benefit from the mechanical method. In a study conducted by Klapproth (2015), teachers' tracking decisions (i.e., decisions according to which students are assigned to different tracks in secondary education) were compared with mechanical models. These models were akin to teachers' decisions in that they were based on the same information teachers are supposed to use when making tracking decisions. It was found that the assignments of students to the different tracks made either by teachers or by the models allowed for the homogenization of the students' achievements for both test scores and school marks. However,

model simulations of tracking decisions were more effective in the homogenization of achievements than were the teachers' tracking decisions. The reason why algorithms produced more homogeneous groups was assumed to be due to the higher consistency of model decisions compared to teacher decisions.

Meijer et al. (2020) recently suggested a simple procedure according to which mechanical decisions could be applied to diverse contexts. They distinguished four steps to reach a mechanical decision: (1) specification of criteria, (2) selection of predictors, (3) collection of information, and (4) the combination of information according to a rule. The application of this procedure should make mechanical decision-making more accessible.

5. CONCLUSION

What can we conclude from the above considerations about decision-making under pressure? First and foremost, decision-makers need to accept that correct decisions are hard to reach. Second, pressure on decision-making is ubiquitous. There is almost always some sort of pressure of a certain amount in the environment that might affect the way information is processed and how decisions are made. In most business situations, knowledge is much less than perfect and uncertainty dominates the scene. Managers and other stakeholders frequently have to reach decisions quickly. Information provided to decision-makers is often either scarce or multifaceted. Considerations about how to cope with difficulties in decision-making lead to the third conclusion: keep it simple! A multitude of research has shown that the quality of decisions improves when decision-makers abstain from using complex and sophisticated algorithms. Instead, they are better off when they apply short heuristics, which are often superior to normative decision models because they are quicker, need less cognitive effort, and cope better with uncertainty. The fourth and final conclusion is: do not trust your gut feelings since they are often wrong and can lead to false decisions. Enrich your intuition by bolstering it with a formal procedure, such that you allow a fixed rule to process the relevant information.

REFERENCES

- Ahituv, N., M. Igbaria, and A. Sella, 1998, "The effects of time pressure and completeness of information on decision making," *Journal of Management Information Systems* 15, 153-172
- Baradell, J. G., and K. Klein, 1993, "Relationship of life stress and body consciousness to hypervigilant decision making," *Journal of Personality and Social Psychology* 64, 267-273
- Bright, L. F., S. B. Kleiser, and S. L. Grau, 2015, "Too much Facebook? An exploratory examination of social media fatigue," *Computers in Human Behavior* 44, 148-155
- Bröder, A., 2000, "Assessing the empirical validity of the 'take-the-best' heuristic as a model of human probabilistic inference," *Journal of Experimental Psychology. Learning, Memory, and Cognition* 26, 1332-1346
- Brunswick, E., 1952, *The conceptual framework of psychology*, University of Chicago Press
- Buckert, M., C. Schwieren, B. M. Kudielka, and C. J. Fiebach, 2014, "Acute stress affects risk taking but not ambiguity aversion," *Frontiers in Neuroscience* 8:82
- Chewning, E. G., and A. M. Harrell, 1990, "The effect of information load on decision makers' cue utilization levels and decision quality in a financial distress decision task," *Accounting, Organizations, and Society* 15, 527-542
- Cohen, S., 1980, "Aftereffects of stress on human performance and social behavior: a review of research and theory," *Psychological Bulletin* 88, 82-108
- Dawes, R. M., and B. Corrigan, 1974, "Linear models in decision making," *Psychological Bulletin* 81, 95-106
- Ellsberg, D., 1961, "Risk, ambiguity, and the savage axioms," *Quarterly Journal of Economics* 75, 643-669
- Endsley, M. R., 1995, "Toward a theory of situation awareness in dynamic systems," *Human Factors* 37:1, 32-64
- Fiedler, F. E., and J. E. Garcia, 1987, *New approaches to effective leadership: cognitive resources and organizational performance*, Wiley
- Freedman, J. L., and D. R. Edwards, 1988, "Time pressure, task performance and enjoyment," in McGrath, J. E. (ed.), *The social psychology of time*, Sage
- Gilbride, T. J., and G. M. Allenby, 2004, "A choice model with conjunctive, disjunctive, and compensatory screening rules," *Marketing Science* 23, 391-406
- Gilbert, D. T., and J. G. Hixon, 1991, "The trouble of thinking: activation and application of stereotypic beliefs," *Journal of Personality and Social Psychology* 60:4, 509-517
- Gigerenzer, G., 2007, *Gut feelings: the intelligence of the unconscious*, Viking Press
- Gigerenzer, G., P. M. Todd, and the ABC Research Group, 1999, *Simple heuristics that make us smart*, Oxford University Press
- Goldstein, D. G., and G. Gigerenzer, 2002, "Models of ecological rationality: the recognition heuristic," *Psychological Review* 109, 75-90
- Grove, W. M., and P. E. Meehl, 1996, "Comparative efficiency of informal (subjective, impressionistic) and formal (mechanical, algorithmic) prediction procedures: the clinical-statistical controversy," *Psychology, Public Policy, and Law* 2, 293-323
- Harreveld, F., E. Wagenmakers, and H. van der Maas, 2007, "The effects of time pressure on chess skill: an investigation into fast and slow processes underlying expert performance," *Psychological Research* 71, 591-597
- Janis, I., and L. Mann, 1977, *Decision making: a psychological analysis of conflict, choice and commitment*, The Free Press
- Kaemph, G. L., G. Klein, M. L. Thordsen, and S. Wolf, 1996, "Decision making in complex naval command-and-control environments," *Human Factors* 38, 220-231
- Kahneman, D., and A. Tversky, 1984, "Choices, values, and frames," *American Psychologist* 39, 341-350
- Klapproth, F., 2015, "Do algorithms homogenize students' achievements in secondary school better than teachers' tracking decisions?" *Education Policy Analysis Archives* 23, 1-18
- Klapproth, F., and P. Schaltz, 2013, "Identifying students at risk of school failure in Luxembourgish secondary school," *International Journal of Higher Education* 2, 191-204
- Kuncel, N. R., D. M. Klieger, B. S. Connelly, and D. S. Ones, 2013, "Mechanical versus clinical data combination in selection and admissions decisions: a meta-analysis," *Journal of Applied Psychology* 98, 1060-1072
- Maule, A. J., 1997, "Strategies for adapting to time pressure," in Flin, R. E. Salas, M. Strub, and L. Martin (eds.), *Decision-making under stress: emerging themes and applications*, Ashgate
- Maule, A. J., G. R. J. Hockey, and L. Bdzola, 2000, "Effects of time pressure on decision-making under uncertainty: changes in affective state and information processing strategy," *Acta Psychologica* 104, 283-301
- Meehl, P. E., 1954, *Clinical vs. statistical prediction: A theoretical analysis and a review of the evidence*, University of Minnesota Press
- Meijer, R. R., M. Neumann, B. T. Hemker, and A. S. M. Niessen, 2020, "A tutorial on mechanical decision-making for personnel and educational selection," *Frontiers in Psychology* 10:3002
- Ordonez, L., and L. Benson III, 1997, "Decisions under time pressure: how time constraint affects risky decision making," *Organizational Behavior and Human Decision Processes* 71, 121-140
- Sauner-Leroy, J. B., 2004, "Managers and productive investment decisions: the impact of uncertainty and risk aversion," *Journal of Small Business Management* 42, 1-18
- Schneider, S. L., and L. L. Lopez, 1986, "Reflexion in preferences under risk: who and when may suggest why," *Journal of Experimental Psychology: Human Perception and Performance* 12, 535-548
- Shafir, E., I. Simonson, and A. Tversky, 1993, "Reason-based choice," *Cognition* 49, 11-36
- Simon, H. A., 1957, *Models of man, social and rational: mathematical essays on rational human behavior in a social setting*, John Wiley and Sons
- Simon, H. A., 1979, "Information processing models of cognition," *Annual Review of Psychology* 30, 363-396
- Simon, H. A., 1993, "Decision making: rational, nonrational, and irrational," *Educational Administration Quarterly* 29, 392-411
- Staw, B. M., L. E. Sandelands, and J. E. Dutton, 1981, "Threat-rigidity effects in organizational behavior: a multilevel analysis," *Administrative Science Quarterly* 26, 501-524
- Todd, P. M., and G. Gigerenzer, 2000, "Précis of simple heuristics that make us smart," *The Behavioral and Brain Sciences* 23, 727-741
- Tversky, A., 1975, "A critique of expected utility theory: descriptive and normative considerations," *Erkenntnis*, 9, 163-173
- Tversky, A., and D. Kahneman, 1974, "Judgment under uncertainty: heuristics and biases," *Science* 185:4157, 1124-1131
- Vecchio, R. P., 1990, "Theoretical and empirical examination of cognitive resource theory," *Journal of Applied Psychology*, 75, 141-147
- von Neumann, J. and O. Morgenstern, 1944, *Theory of games and economic behavior* (third edition), Princeton University Press
- Weber, E. U. and E. J. Johnson, 2009, "Decisions under uncertainty: psychological, economic, and neuroeconomic explanations of risk preference," in Glimcher, P. W., C. F. Camerer, E. Fehr, and R. A. Poldrack (eds.), *Neuroeconomics. Decision making and the brain*, Academic Press
- Yu, V. L., L. M. Fagan, S. M. Wraith, W. J. Clancey, A. C. Scott, J. Hannigan, R. L. Blum, B. G. Buchanan, and S. N. Cohen, 1979, "Antimicrobial selection by a computer," *Journal of the American Medical Association* 242, 1279-1282
- Zakay, D., 1993, "The impact of time perception process on decision making under time stress," in Svenson, O., and A. J. Maule (eds.), *Time pressure and stress in human judgment and decision making*, Plenum Press

© 2021 The Capital Markets Company (UK) Limited. All rights reserved.

This document was produced for information purposes only and is for the exclusive use of the recipient.

This publication has been prepared for general guidance purposes, and is indicative and subject to change. It does not constitute professional advice. You should not act upon the information contained in this publication without obtaining specific professional advice. No representation or warranty (whether express or implied) is given as to the accuracy or completeness of the information contained in this publication and The Capital Markets Company BVBA and its affiliated companies globally (collectively "Capco") does not, to the extent permissible by law, assume any liability or duty of care for any consequences of the acts or omissions of those relying on information contained in this publication, or for any decision taken based upon it.

ABOUT CAPCO

Capco is a global technology and management consultancy dedicated to the financial services industry. Our professionals combine innovative thinking with unrivalled industry knowledge to offer our clients consulting expertise, complex technology and package integration, transformation delivery, and managed services, to move their organizations forward.

Through our collaborative and efficient approach, we help our clients successfully innovate, increase revenue, manage risk and regulatory change, reduce costs, and enhance controls. We specialize primarily in banking, capital markets, wealth and asset management and insurance. We also have an energy consulting practice in the US. We serve our clients from offices in leading financial centers across the Americas, Europe, and Asia Pacific.

WORLDWIDE OFFICES

APAC

Bangalore
Bangkok
Gurgaon
Hong Kong
Kuala Lumpur
Mumbai
Pune
Singapore

EUROPE

Berlin
Bratislava
Brussels
Dusseldorf
Edinburgh
Frankfurt
Geneva
London
Munich
Paris
Vienna
Warsaw
Zurich

NORTH AMERICA

Charlotte
Chicago
Dallas
Hartford
Houston
New York
Orlando
Toronto
Tysons Corner
Washington, DC

SOUTH AMERICA

São Paulo



WWW.CAPCO.COM



CAPCO