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Title:

Cognitive Flexibility and Adaptive Decision-Making: Evidence from a laboratory study of expert decision-makers

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Cognitive Flexibility and Adaptive Decision-Making

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Abstract

Research summary:

How can strategic decision-makers overcome inertia when dealing with change? In this paper we argue that cognitive flexibility (i.e. the ability to match the type of cognitive processing with the type of problem at hand) enables decision-makers to achieve significantly higher decision-making performance. We show that superior decision-making performance is associated with using semi-automatic Type 1 cognitive processes when faced with well-structured problems, and more deliberative Type 2 processes when faced with ill-structured problems. Our findings shed light on the individual-level mechanism behind organizational adaptation and complement recent work on strategic inertia. In addition, our findings extend management studies that have stressed the relevance of cognitive flexibility for responding to the demands of increasingly open, flexible, and rapidly changing organizations.

Managerial summary:

Humans are creatures of habits. We tend to prefer known courses of action over new ones. In many cases, habits are good. However, when things change in unpredictable ways, the past may not be good guidance for the future. We argue that "cognitive flexibility" -the ability of understanding when to rely on habits vs. when to explore new courses of action- enables managers to switch from a "fast" decision mode, based on habits, to a "slow", more deliberate decision mode that facilitates the exploration of new courses of action. Managers high in cognitive flexibility reflect on the situation at hand, recognize and value diversity in viewpoints, and integrate such diversity in their own decision processes. By valuing diversity, they are more likely to overcome inertia.

Introduction

Strategic change is difficult. Even when organizations recognize the need to change, they are often unable to act, and fall prey to inertia. The inability to engage in adaptive decision-making has proven particularly detrimental to established firms (Tripsas and Gavetti, 2000). However, young firms are also challenged by strategic changes (Gruber, MacMillan, and Thompson, 2012; Rerup and Feldman, 2011). In both contexts, the cognitive abilities of key decision-makers are a crucial factor in explaining strategic adaptability and, ultimately, success (Adner and Helfat, 2003; Eisenhardt, Furr, and Bingham, 2010; Sharfman and Dean Jr, 1997; Thomas , Clark, and Gioia, 1993).

Research has shown that the ability to adapt to changing environmental problems is critical for strategic decision-makers (Barr, Stimpert, and Huff, 1992; Gavetti, 2005; Gavetti and Levinthal, 2000; Hodgkinson, 1997; Joseph and Ocasio, 2012; Levinthal and March, 1993). However, little is known about the individual-level mechanisms behind this ability, or its impact on performance. Responding to recent calls to analyze the origins and characteristics of "managerial cognitive capabilities" (Helfat and Peteraf, 2015), we study the individual-level mechanism through which decision-makers match their mode of cognitive processing to the task environment. We argue that *cognitive flexibility* makes certain individuals better at adapting their cognitive processing to different types of problems. Definitions of cognitive flexibility vary from an “ability to generate broad or narrow categorizations of stimuli depending on appropriateness” (Murray *et al.*, 1990) to the plasticity required to adjust to new environmental demands (Furr, 2010; Salisbury, 2003). We build on these ideas by defining cognitive flexibility as the ability to match the type of cognitive processing with the type of problem at hand. This matching depends on two conditions being met. First, decision-makers need to be able to describe the type of problem they face, which requires the *identification* of different elements, views, and perspectives of a situation. Second, decision-makers need to consider different possibilities, which requires active *reflection* on the elements identified to find possible connections and judge their appropriateness (Diamond, 2013; Raes *et al.*, 2011). Cognitive flexibility is important because “If a decision maker wanted to achieve both a reasonably high level of accuracy and low effort, he or she would have to use a repertoire of strategies, with selection contingent upon situational demands” (Payne, Bettman, and Johnson, 1988, p. 539).

In line with previous research in strategic management (Hodgkinson and Healey, 2011; Levinthal and Rerup, 2006; Louis and Sutton, 1991) and the cognitive sciences (Evans and Stanovich, 2013; Lieberman, 2007), we frame our discussion in terms of the interplay between two types of cognitive processing. We argue that decision-makers use cognitive flexibility to switch between these processes to solve problems (Deak, 2004), and show that individuals with high cognitive flexibility achieve significantly higher performance in different types of problems.

Below, we present the concept of cognitive flexibility, then develop our theoretical model and test it in a sample of experienced decision-makers. Finally, we discuss our results and contributions.

Cognitive flexibility in strategic management and the cognitive sciences

Over the last decade, cognitive approaches to strategy have studied how attention drives cognitive processes that lead to more or less stable patterns of interpreting the environment. These, in turn, impact organizational action and adaptation to changing circumstances (Ocasio, 1997, 2011; Sharfman and Dean Jr, 1997). Knowing how people adapt to changing circumstances is crucial to understanding how strategic decision-makers overcome *cognitive inertia*—defined as an over-reliance on certain mental models that undermines the organization's ability to notice and adapt to changes (Hodgkinson, 1997; Hodgkinson and Wright, 2002). Several researchers have empirically analyzed the relationship between cognitive inertia and lack of adaptation (see, e.g. Barr and Huff, 1997; Barr *et al.*, 1992; Hodgkinson, 1997; Hodgkinson and Sparrow, 2002; Reger and Palmer, 1996; Tripsas and Gavetti, 2000), and there is now ample empirical evidence that strategic flexibility drives firm performance (Barr *et al.*, 1992; Gavetti, 2005; Gavetti and Levinthal, 2000; Grewal and Tansuhaj, 2001; Levinthal and March, 1993; Nadkarni and Narayanan, 2007; Worren, Moore, and Cardona, 2002). Scholars have argued that such flexibility comes mainly from decision-makers: As they update their mental representations, so they can explore, and act upon, alternative behaviors and options (Louis and Sutton, 1991; Marcel, Barr, and Duhaime, 2011). Strategic decision-makers' ability to update their mental representations in response to changes in the external environment is therefore a critical capability (Barr *et al.*, 1992; Gavetti, 2005; Gavetti and Levinthal, 2000; Hodgkinson and Healey, 2011; Levinthal and March, 1993; Reger and Palmer, 1996; Schwenk, 1988; Teece, 2007).

To update their mental representations, strategic decision-makers must first engage in "cognitive shifts" and adapt their cognitive processes to the specific situation (Foldy, Goldman, and Ospina, 2008; Mom, Van Den Bosch, and Volberda, 2007). If a situation involves problems that are well-structured, with known alternatives, strategic decision-makers can benefit from reacting rapidly, drawing on experience and learned behaviors. However, faced with problems that are ill-structured, with unknown options, they are more likely to benefit from reflecting, analyzing, and deliberating.

Even when decision-makers can see that their usual responses may not work, their potential for change is very limited if they do not adjust their cognitive processing (Betsch *et al.*, 2001; Dane, 2010; Grégoire, Barr, and Shepherd, 2010; Verplanken and Faes, 1999). Cognitive flexibility can help overcome cognitive inertia by allowing decision-makers to adjust their processing mode to different situations. Research has proposed that this happens in two steps: first, by *identifying* different problem elements and their discontinuities, and second, by *reflecting* upon the connections between elements to untangle cause-and-effect relationships (Raes *et al.*, 2011). In particular, Raes *et al.*'s (2011) conceptual paper considers cognitive flexibility in the context of the interactions between top and middle managers, finding that more cognitively flexible individuals develop a broader variety of interpretations and perspectives, leading to superior performance. Furr, Cavarretta, and Garg (2012) explore the concept of cognitive flexibility at the level of the individual decision-maker, defining it as the characteristics and processes that allow individuals to collect and integrate new information, reflect upon it, and modify their perspectives. Shaffer *et al.* (2012) show that those who work in several countries require greater cognitive flexibility, to match their mental processes to the situational demands of different cultures (Shaffer *et al.*, 2012). Bledow, Rosing, and Frese (2013) explore the potential of cognitive flexibility in creativity and idea generation.

Cognitive flexibility is related to, yet distinct from, other concepts used in cognitive and social psychology. For example, two related streams of analysis rely on the concepts of cognitive complexity (Scott, 1962) and integrative complexity (Tetlock, Peterson, and Berry, 1993). Cognitively complex individuals are better at understanding problems with more independent dimensions. Integratively complex individuals tend to consider multiple points of view, identify novel and creative solutions, and avoid making quick or routinized decisions or jumping to conclusions. Yet both these types of complexity are unvarying—i.e. no matter how simple or complex the problem itself may be, people in either category would always frame it as if it were made up of many interrelated parts (cognitive complexity) or consider multiple points of view (integrative complexity). Cognitive flexibility, in contrast, is about *adapting* the processing style to the problem.

Prior work in cognitive psychology has identified a number of trait-like features that describe how people make "cognitive shifts." For example, Tetlock, Peterson, and Lerner (1996) discussed the differences between integratively simple and integratively complex individuals. Kirton (1989) framed the discussion in terms of the distinction between innovators and adaptors. Many other ways of categorizing individuals exist. These approaches share an emphasis on the intrinsic characteristics that set people apart, potentially allowing them to achieve superior decision-making performance in comparison with other categories of people. In other words, Kirton's adaptors are always adaptors, regardless of the problem they face. Our approach focuses, instead, on the possibility that (some) people may be able to change how they approach a given problem. In this sense, we posit that cognitive flexibility can show how to overcome inertia.

While research has linked cognitive flexibility and the ability to adapt to varied problems, we lack an in-depth understanding of the individual-level mechanisms behind it. To approach this issue, we need to solve both empirical and conceptual problems. On the empirical side, operationalizing cognitive flexibility is difficult. Self-reported measures such as the Cognitive Flexibility Scale (Martin and Rubin, 1995; Martin, Staggers, and Anderson, 2011) are practical in many settings, but also entail disadvantages such as social desirability bias and a reliance on individuals' introspective ability (Podsakoff and Organ, 1986). Two main tasks have been used in the literature to measure cognitive flexibility: the Stroop task and the Wisconsin Card Sorting Task. Although these tests have a long history and much visibility in the problem-solving literature, they were originally developed for clinical use, to assess patients who failed to adjust to new problem settings or rules. Therefore, their use in healthy individuals remains problematic, since participants might find them too easy (and hence lose motivation), and it is difficult to trace inter-individual differences as participants are very likely to reach ceiling effects. Others have used proxy measures that capture one aspect of cognitive flexibility, such as the number of categories identified while generating ideas (Bledow *et al.*, 2013). A shortcoming of such indirect approaches is that they tend to focus on a single aspect of cognitive flexibility, and thus may fail to capture the variety of aspects involved.

On the conceptual side, one problem is the lack of clear categories to define the micro-level processes that individual use to switch. Hodgkinson and Clarke (2007) suggested that certain individuals "possess in equal abundance the inclination to attend to analytic detail and cut through that detail, as and when required" (Hodgkinson and Clarke, 2007, p. 247). This intuition is consistent with work in cognitive science, where cognitive flexibility explains our ability to generate broad or narrow categorizations of stimuli depending on appropriateness (Murray *et al.*, 1990), through "mental set shifting" (Goel and Vartanian, 2005, p. 1175). Here, cognitive flexibility lies at the core of human adaptation, and is the hallmark of human cognition and intelligent behavior[1] (Deak, 2004; Evers *et al.*, 2007; Goel and Vartanian, 2005; Kamigaki, Fukushima, and Miyashita, 2009). Cognitive scientists tend to agree that the key mechanism that allows for cognitive flexibility is the ability to alternate between processing types (Diamond, 2013; Evans and Stanovich, 2013).

As summarized in Kahneman (2011), dual-process theories have long differentiated between two qualitatively distinct types of cognitive processes (Cohen, 2005; Cohen, Dunbar, and McClelland, 1990; Kahneman and Treisman, 1984; Posner and Snyder, 1975; Shiffrin and Schneider, 1977). On one hand, there are the highly specialized "automatic" processes, which are very fast and require little or no cognitive control. On the other hand, there are slower, deliberate, and controlled processes. This idea has also found its way into the decision-making and economic literatures, where a distinction has been made between Type 1[2] and Type 2 processes (Camerer, Loewenstein, and Prelec, 2005; Kahneman, 2003; Stanovich, 1999). Type 1 processing corresponds closely to automatic processing; it is faster, has higher capacity, and proposes intuitive answers to problems as they arise. Type 2 processing corresponds to controlled processes; it is slower, has a limited capacity, and provides reflective answers.

There are two major accounts of how the different processing types operate. The parallel-competitive form assumes that Type 1 and 2 processing operate in parallel, each having their say, with conflict resolved if necessary (Healey, Vuori, and Hodgkinson, 2015; Smith and DeCoster, 2000). In contrast, default-interventionist theories assume that rapid Type 1 processing generates intuitive default responses first, on which subsequent reflective Type 2 processing may or may not intervene (Evans and

[1] Note that cognitive flexibility is not "intelligence." Cognitive flexibility refers to mental set shifting, which is considered an important aspect of (fluid) intelligence, but not the only one. See, for example, (Miyake and Friedman, 2012). Generally, one would expect cognitive flexibility to be positively correlated with measures of intelligence, but such correlations will be most likely weak and varying depending on the specific proxy of intelligence one chooses.

[2] The literature also uses the terms "System 1" and "System 2," or "intuitive" and "deliberative." In his 2011 work, Kahneman refers several times to the work of Keith Stanovich and collaborators, relying on the differentiation between two "systems." However we follow Evans and Stanovich (2013) in avoiding the "system" terminology, because it can falsely suggest that the two types of process are located in two specific neurological "systems." In fact, there is no neurological evidence for these two process types being neurologically separate,, so using "Type" terminology enables us to indicate qualitatively distinct forms of processing without making any additional assumptions about their neurological location.

Stanovich, 2013; Kahneman, 2011; Kahneman and Frederick, 2002; Mishra, Mishra, and Nayakankuppam, 2007). Given its current psychological and neuroscientific support, we rely on the default-interventionist mode, which assumes that Type 2 processing acts in addition to Type 1 processing. Table 1 summarizes the main characteristics of the two types of cognitive process based on contemporary research in neuroscience and psychology (Evans and Stanovich, 2013; Kahneman, 2011; Lieberman, 2007).

Insert table 1 about here

Much attention has been paid to both Type 1 and Type 2 processing, but far less to the switch between them. To fill this gap, we propose and test a model of adaptive decision-making, whereby decision-makers use cognitive flexibility to adapt their mental processes to varying task environments. In this model, cognitive flexibility is decision-makers' ability to match the type of cognitive processing with the type of problem at hand. We argue that an individual's effectiveness is not determined solely by how well they function in either Type 1 or Type 2 processing, or how long they spend in either mode, but by how they use cognitive flexibility to match cognitive processing to problem demands (Deak, 2004).

Model and hypothesis development

Our empirical strategy builds on Nickerson and Zenger's (2004) idea that a manager's "job" can be decomposed into multiple problems, each of which can be further decomposed to some degree. A representative day of a manager's life is partitioned into small blocks of time, and they must constantly switch their attention. Even when the manager faces a "big" problem, their thinking periods are brief—partly because their attention span is limited, and partly due to interruptions. As a result, their brain is constantly decomposing problems into smaller chunks and dealing with them in sequence, in a process termed "recursive decomposition" (Baumgartner and Payr, 2014). Consider how we multiply two three-digit numbers: we separate the problem into smaller chunks, solve them separately, and then recombine them (see also "Empirical design" in the online appendix).

In Mintzberg's classic study, half of managers' activities last 90 minutes or less, and only one-tenth of their tasks last an hour or more (Mintzberg, 1973). With increasing hyper-connectivity and pressure to respond quickly, sustained task focus is even harder than in the early 1970s. One study found that individuals in the workplace focused for 3m 5s on a single task before switching, and switched between problems every 12 minutes, on average (González and Mark, 2004).

In the cognitive sciences, a research stream called "task switching" or "mental set" tries to answer: What happens when individuals try to switch rapidly between one task and another? Another stream of literature, called "divided attention" or "dual-task performance," tries to answer: What happens when individuals try to do more than one task at the same time (Pashler, 2000)? In line with our argument so far, we study how individuals switch between problems sequentially rather than solving them in parallel. In taking this approach, we build on a widely accepted decision-making model (Beach and Mitchell, 1978) where the individual receives a stimulus, selects Type 1 or 2 processing, and achieves better task performance if their choice is consistent with the demands of the problem at hand. Figure 1 represents this model and our three hypotheses, which we develop below.

Insert figure 1 about here

Starting with the Beach and Mitchell (1978) model, we add cognitive flexibility, which affects which processing type is activated. In real life, different stimuli are presented to the individual, so they may (or may not) update their processing to fit the task. If this means they match their processing to the problem, they will be adaptive, and can be considered cognitively flexible (Deak, 2004). In sum, as Raes *et al.* (2011) put it, cognitive flexibility supports “decisions that are *optimally tailored* to the environment rather than decisions based on more general assumptions and interpretations” (Raes *et al.*, 2011, p. 111, emphasis added). Hence our first hypothesis:

HYPOTHESIS 1. *Individuals with higher levels of cognitive flexibility will achieve higher decision-making performance.*

What are “optimally tailored” decisions? To answer this question, we need a way to categorize the decision-making situations, or task environments, to which the processing mode needs to be tailored. To do so, we identify two fundamentally distinct classes of problems, drawing on prior work (see, e.g. Simon, 1974). *Well-structured* problems are those in which a strategic decision-maker faces uncertainty about outcomes in a context in which the current and end states are clearly identified, and the options and methods to identify a solution are known (through experience) or knowable (through computation) (Klein, 1999). Conversely, *ill-structured* problems are those where there is great uncertainty about both current and end states. No repertoire of solutions (or methods to identify them) is available, and they need to be learned or discovered. We contend that these two types of problems require different processing modes.

A groundbreaking article by Taylor and Fiske (1978), for example, reviewed work indicating that automatic cognitive responses will lead to enhanced performance in a variety of situations (what the authors called "top of the head" phenomena). Well-structured problems tend to be repetitive, and may be approached by relying on experiential associations based on past experiences with comparable tasks (Kahneman and Klein, 2009; Salas and Klein, 2001; Shiffrin and Schneider, 1977). It appears that when the environment provides a problem that is well structured, that problem will be represented in a simple way, and a faster, semi-automatic type of processing (Type 1) will allow the individual to identify appropriate solutions. Consequently, their performance is likely to be high. Research in management has also emphasized the importance of semi-automatic, routine-based behavior (Cacciatori, 2012; Cohen and Bacdayan, 1994; Feldman, 2000; Feldman and Pentland, 2003; Nelson and Winter, 1982). Relying on more automatic, routine-based behavior enables organizational members to conserve limited cognitive resources by deploying tried and tested solutions. Hence, we propose:

HYPOTHESIS 2a. *In a well-structured task, Type 1 processing is associated with higher performance.*

Conversely, for an ill-structured task, more deliberate mental processes will be needed, and processing will follow a slower, less automated mode (Type 2 processing). The complexities of the task, the generation of potential alternatives, and the many possible cause-and-effect relationships inherent in the problem-solving process will slow down decision-making. In particular, since alternative options are not predefined, the individual must generate and evaluate alternative states of the problem, their outcomes, and their impacts—on the individual themselves, and on others (Payne, Bettman, and Johnson, 1993).

Indeed, failure to consider others' perceptions will lead them to neglect factors (i.e. others' response to proposed changes) that might lead to cognitive inertia.

Strategic change is a prototypical event that requires more Type 2 processing (Kim, Hornung, and Rousseau, 2011; Louis and Sutton, 1991). The emergence and evolution of macro-level constructs, such as dynamic capabilities, has been associated with adopting more deliberate forms of cognition at the organizational level (Levinthal and Rerup, 2006; Zollo and Winter, 2002). Research into crisis response management backs this up—see, for example, Klein's discussion about the role that "mental simulations" play "in nonroutine decision tasks" (Klein, 1999, p. 89). In the cognitive sciences, McClure *et al.* (2004) reported that decisions involving deferred reward required the mental simulation of future possibilities, and hence relied more on Type 2 processes, while decisions about immediate reward relied predominantly on Type 1 processes. Similarly, Greene *et al.* (2004) found that when participants reasoned over the consequences of alternatives during trials, they took far longer to produce their responses. Following the default-interventionist logic, we propose that in ill-structured tasks, it is more likely that Type 1 responses may not be adequate, and will therefore require a Type 2 intervention (Evans and Stanovich, 2013; Kahneman, 2011; Kahneman and Frederick, 2002). Hence we hypothesize:

HYPOTHESIS 2b. *In an ill-structured task, Type 2 processing is associated with higher performance.*

Now, one might argue that decisions based on Type 2 processing generally obtain higher performance than those based on Type 1 processing, as individuals benefit from reflecting on their actions and evaluating the options provided by Type 1 processing. However, individuals do not always have the time or mental resources to apply slow, deliberate processing. Moreover, even if time and resource were plentiful, would additional deliberation *always* mean higher performance? Past studies have shown that pushing for an apparently rational choice (and therefore deliberating more) can sometimes impair performance (Klein, 1999, p. 31). Hodgkinson and Healey (2011) reported the example of a failed IT system change at the London Stock Exchange, where the initial, intuitive solution was better than the more deliberate one that was actually adopted, at a high cost in time and resources. Payne et al. (2008) found time pressure to be a boundary condition for the effectiveness of Type 2 processes, which chimes with the recent discussion of “simple rules” in strategic decision-making (Bingham and Eisenhardt, 2011).

Cognitive flexibility avoids such traps by facilitating “cognitive shifts” (Foldy et al., 2008; Mom et al., 2007). It allows decision-makers to identify the elements and possibilities of a situation, reflect on their possible connections, and switch gears to the appropriate behavior (Louis and Sutton, 1991). On one hand, when facing an ill-structured problem, the individual must first understand that relying on habits of mind, routines, heuristics, or automatic processing is not enough, then incorporate a more deliberate mode of processing. On the other hand, when the environment presents a well-structured problem, cognitive flexibility signals that active thinking is superfluous, and that a more automatic type of processing is required. Having perceived elements, possibilities, and connections, decision-makers must develop simple routines or heuristics to guide their behavior (Bingham and Eisenhardt, 2011). We therefore propose that cognitive flexibility is a moderator of the relationship between the type of problem and type of processing:

HYPOTHESIS 3. *The higher the cognitive flexibility, the more likely the use of Type 1 processing in a well-structured task and Type 2 processing in an ill-structured task.*

Methods

A summary of our model operationalization is presented in Figure 2. For each participant we measured their cognitive flexibility and exposed them to two different problem types (i.e., well-structured and ill-structured). In addition, for each problem type, we assessed the type of processing participants engaged in (proxied by their response time) and their performance (a score). All data is available from the authors upon request.

Insert Figure 2 here

Sample

Our study participants comprised 49 strategic decision-makers (senior executives in multinational companies, founders of small companies, and unit managers in medium-sized organizations). All had at least four years’ experience in managerial decision-making; participants were required to have job responsibilities that included budget-allocation decisions, and to lead a group with at least two other members. The sample consisted of 40 males and nine females, and the mean age was 35.00 (s.d. = 6.74). In an effort to increase participants' motivation, and bearing in mind that our participants are experienced decision-makers with high opportunity cost for their time, we offered both non-monetary and monetary incentives (for details, see "Incentives" in the online appendix).

To screen for factors that could affect cognitive flexibility, performance, or both[3], we selected participants according to several criteria. First, all participants had comparable managerial experience (5–12 years). Second, all held bachelors' degrees in science- and engineering-related subjects, and most also had a masters degree. Third, all participants shared managerial responsibilities for leading others. In addition, all participants were screened to identify individuals who had abnormal levels of stress or anxiety, suffered from psychiatric disorders, or were on any psychiatric medications. All volunteers met the criteria for inclusion and none had to be excluded. In addition, we controlled for standard variables, such as age and gender, and these were included in our regression analyses.

Tasks

Most research in strategic management and the cognitive sciences has examined problem-solving by varying the attributes of a single problem: difficulty, complexity, available time, and so on (Goel, 2009; Jonassen, 1997). In the present study, in contrast, we tested between-task flexibility: that is, the ability to switch cognitive processing type across different problems (Hassin, Bargh, and Zimerman, 2009). We presented participants with two very different types of problem (one well-structured, one ill-structured) and measured an individual-level ability (cognitive flexibility) to understand how it influences the matching of processing type to problem type.

[3] Such screening is particularly important given that we did not design a randomized study, but instead wished to capture individuals' natural abilities and performance. Thus, we followed strict screening procedures to ensure the sample participants did not suffer from psychiatric conditions found to affect cognitive flexibility (e.g. anxiety, schizophrenia, obsessive compulsive disorder). In addition, another factor found to affect cognitive flexibility is age: cognitive flexibility significantly decreases in participants older than 70 years. Our sample's age falls well below that threshold.

For the well-structured problem, we relied on the computerized "four-armed bandit" game, where participants must maximize their winnings by choosing between four slot machines (or "slots") offering varying unknown payoffs. This task has been used in multiple management studies to explain the antecedents and consequences of decisions (Denrell and March, 2001; Laureiro-Martinez, 2014; Laureiro-Martínez *et al.*, 2014; March, 2003; Meyer and Shi, 1995; Posen and Levinthal, 2012). For the ill-structured problem, we used a "think-aloud" protocol (Grégoire *et al.*, 2010; Isenberg, 1986; Sarasvathy, Simon, and Lave, 1998; Sarasvathy, 2001) inspired by the "Hungeria" problem by Fernandes and Simon (1999), which meets the criteria of complexity and uncertainty in terms of both outcomes and alternatives, and thus allows for a wide variation in strategies. It required participants to imagine they were the leader of a small aboriginal tribe who must safeguard the community from external invaders. (A full description of both tasks is included in the "Research materials" section of the online appendix.)

It was critical to select two problems that differed in terms of providing alternatives. In Task 1, despite the computational complexity of the payoff function, the four alternatives (slots) are given and the possible actions defined (persist with the same slot, or switch to an alternative one). In Task 2, participants had to create the alternatives themselves from the situation they were given. This requirement for participants to generate alternatives themselves was important, because we needed the toughest test for our hypotheses. For example, we could have compared the results of a two-armed vs. a four-armed bandit. Since the latter is more complex than the former, it would require more Type 2 processing and deliberation. But such an increase could be down to an ability acquired when playing the simpler bandit game, which is then transferred to the more complex one. With two very different tasks, we eliminate the effect of familiarity or experience, so any switch is more likely to be related to cognitive flexibility, rather than a reflection of mere skill acquisition through learning from prior experience.

Measures

Processing types: processing time 1 and processing time 2

Difference in response time (or speed of execution) has long been used to distinguish between Type 1 and Type 2 processes (Atkinson, Holmgren, and Juola, 1969; Shiffrin and Schneider, 1977) and has become the most commonly accepted measure: Type 1 processes are fast, while Type 2 processes are slow[4] (Evans and Stanovich, 2013). Speed has been identified as a principal indicator of routinization (Cohen and Bacdayan, 1994; Weiss and Ilgen, 1985). Cognitive psychologists and neuroscientists have long agreed that creating behavioral repertoires of standard solutions allows individuals to simplify their decision-making process and, thus, respond more quickly. The converse is also true: if a decision requires complex deliberation, the response time is longer (Atkinson *et al.*, 1969; Cavanagh, Labianca, and Thornton, 2001; Neuberg and Newsom, 1993; Shiffrin and Schneider, 1977). Hence, we used the time it took participants to solve each problem as a proxy for the type of process they were using. We ensured the validity of our measures in three ways.

First, all participants were given exactly the same instructions and controlled conditions. The instructions and think-aloud training for Task 2 were carefully pilot-tested to ensure the collected data was independent from the talkativeness of the participant. In a review of more than 40 studies, Ericsson and Simon (1993) found that participants could take somewhat longer to complete the tasks while thinking aloud, presumably because of the time needed to vocalize their thoughts. However, there was no evidence that thinking aloud affected performance.

Second, each task involved different time windows: Task 1 was delimited by shorter time intervals, given the simplicity of each individual choice, while Task 2 had an upper limit of two hours.

Third, despite the different time windows, our design allowed for significant variance and also for enough time slack (to reduce or exclude time pressure). In Task 1, the mean total thinking time for all 300 trials was 7.14 minutes and the standard deviation 0.48 minutes. Per decision, participants took 1.42 seconds on average (standard deviation 0.0956 seconds). Some participants answered very quickly on average (6.48 minutes in total) while others took longer (8.98 minutes in total). The total allotted time they had available was 12.5 minutes, ensuring they all enjoyed plenty of slack. In Task 2, the mean thinking time was 13.3 minutes and the standard deviation 10.8 minutes. Some participants arrived at what they

[4] As encapsulated by the title of Kahneman's (2011) famous book: *Thinking Fast and Slow*.

considered a satisfactory solution in around 2.2 minutes, while others took much longer (one participant took 51.2 minutes). Here, too, slack was plentiful: The limit of 120 minutes was twice the time required by the slowest participant in our pilot tests.

Using response times as a continuum variable is simpler, and also means that we do not have to impose an arbitrary threshold between "fast" and "slow" responses (i.e., Type 1 and 2 processing). This operationalization is consistent with classic studies in psychology (Kahneman, 2011; Kahneman and Frederick, 2002), cognitive sciences (Evans and Stanovich, 2013; Luce, 1991), and management (Cohen and Bacdayan, 1994; Laureiro-Martinez, 2014). However, we consider the limitations of this approach, and alternatives, in the Discussion section.

Response: Task 1 and Task 2 scores

Past research has found that well- and ill-structured problems require different sets of skills and processes, and therefore performance should be evaluated independently, taking into account the different problems' objectives (Jonassen, 1997; Shin, Jonassen, and McGee, 2003; Sigler and Tallent-Runnels, 2006). The objective for Task 1 was defined as "score as many points as you can," while for Task 2 it was "keep your tribe safe." Performance in Task 1 was measured with each participant's total cumulative score. The measure of performance in Task 2 accounted for the fact that multiple solutions are possible, and that this may not be readily apparent in the protocol. We therefore relied on two research assistants with significant experience in content analysis, who independently scored Task 2 performance based on how well the participant's solution fulfilled the problem's objective. We used conventional content analysis involving coders immersing themselves in the data to allow new insights to emerge from systematic comparisons across the protocols (Ericsson, 2006; Kondracki, Wellman, and Amundson, 2002). Coders followed a sequence of steps to ensure they gleaned information directly from the participants' solutions, without imposing preconceived categories or theoretical perspectives (Hsieh and Shannon, 2005). First, they read all the protocols to achieve immersion and obtain a sense of the whole. Next, they were directed to code the final paragraph of the protocol itself, reporting the stated solution as identified by each participant. They then made notes of their impressions, thoughts, and initial perceptions of whether the solution achieved the task objective. Next, they classified the solutions into three broad categories: "solved the problem and reached the objective," "somewhat likely to achieve the objective," and "unlikely to achieve the objective." Only once this was completed did they re-read the protocols and score each one from 1 to 10, based on how likely it was that it would fulfill the objective. We calculated a measure of performance for each protocol as the mean score given by the two research assistants.

On Task 1, participants scored an average of 18067 points (s.d. = 594). The lowest score was 15356, and the highest was 18795. On Task 2, scores ranged from 4 to 9, with an average of 5.98 (s.d. = 1.07). To allow for a comparison across the two tasks, we standardized the variables, rescaling each to have a mean of 0 and a standard deviation of 1. We added the two scores to create a unique performance measure that summarized how well a participant performed in solving both problems.

Cognitive flexibility measure

Consistent with the definitions used in management studies (Raes *et al.*, 2011), the cognitive sciences (Diamond, 2013; Kamigaki *et al.*, 2009), and the ethnographic tradition in cultural anthropology (Appadurai, 1996; Hannerz, 1992), we built a code to operationalize cognitive flexibility in its two main analytical categories: *identification of key problem elements* and *reflective perspective*. The former relates to the ability to identify the essential elements of the problem context, which requires taking diverse information and perspectives into account (Diamond, 2013; Raes *et al.*, 2011). A *reflective perspective* relates to the ability to reflect on these elements, consider the connections among them, and potentially change how one thinks about something. In combination, these two analytical categories are more likely to induce "cognitive shifts" to the appropriate type of processing (Foldy *et al.*, 2008; Mom *et al.*, 2007).

Following the recommendations by Duriau, Reger, and Pfarrer (2007), the code was constructed in collaboration with a cultural anthropologist[5] and a research assistant. Both the analytical categories were operationalized in a set of specific codes, presented in Table 2. Each time a protocol from Task 2 was found to contain a statement relating to any one of these codes, we interpreted it as an instance of the

[5] The anthropologist had prolonged first-hand experience in qualitative research, working with different communities in several different countries, and had the knowledge and expertise (i.e., the code) required to isolate, at the code level, the analytical categories that capture cognitive flexibility.

corresponding category. For example, if a participant pondered how someone else would frame the problem, they demonstrated awareness of the existence of alternative takes on the situation. Therefore, the coders would code the statement under the first category listed in Table 2 and alter the participant's cognitive flexibility score accordingly: Items 1–6, 9, and 10 were positively associated with cognitive flexibility and added points, while items 7 and 8 were negatively associated and subtracted points.

Insert Table 2 about here

A group of four coders was trained by the same anthropologist who had helped to develop the codes in Table 2. For each individual's protocol, the unit of analysis was the meaningful phrase. During training, we clarified that the code did not aim to capture *emotional empathy* (also called "affective empathy") or the level of imagination participants displayed in their solutions. Each coder conducted the coding process independently using *NVivo,* a software for qualitative data analysis (Ltd., 2012).

Additional control questions

After participants finished the tasks, we asked control questions to exclude advantages in experience or familiarity with the tasks. We investigated their involvement in certain non-professional activities that could have affected their performance in the tasks. For Task 1 we probed their experience in computer/video/smartphone games, gambling, or gambling games. None of the participants played games more than once a week or gambled regularly. For Task 2 we asked them if they had been involved with isolated communities (unlikely, but still possible), done recent NGO work, and whether they watched a lot of ethnographic documentaries; none had. We asked all participants whether they were familiar with either of the tasks, or whether they were familiar with the context of Task 2, which might have biased them towards providing a richer solution; none were. Participants performed a Raven's test, a commonly used proxy for general intelligence (Raven, Raven, and Court, 2003)

Assessment of the validity and reliability of the think-aloud exercise and the coding procedures

To assess whether participants effectively verbalized their thoughts, we asked them to summarize their thinking and proposed solution at the end of each verbalization. Participants' retrospective verbalizations were highly convergent with what they had said in the think-aloud protocols, supporting the internal validity of the protocols (Ericsson and Simon, 1993; Grégoire *et al.*, 2010).

Consistent with the commonly accepted standards of verbal protocol and content analysis (Krippendorff, 2004; Neuendorf, 2002), each coder coded the data independently. In addition, they did not participate in the study in any other way, and were blind to our theory and hypotheses (Sarasvathy, 2001). They were trained on eight protocols that were part of the pilot-test data and were only provided with the study data once they had satisfactorily completed the training phase. Each verbal protocol was coded by a total of five coders.

First, to code for cognitive flexibility, protocols were randomly assigned to three of four coders. This spread the work among the four individuals and mitigated any possible biases. We compared the results of their coding and calculated inter-rater reliability indexes. Testing the coders' reliability reduced the potential subjectivity problem generated by the coding scheme and variables. Simpler coding strategies, where coders must identify appearances of specific words or phrases, provide high levels of agreement among coders. When coding is more demanding, past research has proposed that more liberal criteria are used for indices such as Cohen's K, which are known to be more conservative (Lombard, Snyder-Duch, and Bracken, 2002; Neuendorf, 2002). In our case, three coders had to interpret complex streams of verbalized thoughts, making coding more demanding. The authors developed the code and trained the coders, but did not code the protocols. All indexes were computed right after all coders completed their task, without any round of alignment. Given this very strict coding procedure, we obtained acceptable levels of agreement among coders: 93.37 percent agreement and Cohen's K of 0.52.

Second, to code for performance, two coders (not from the first group) were assigned all 49 protocols. Each coder independently assigned a score to each protocol. We then calculated a basic inter-rater reliability coefficient, which indicated acceptable reliability (92.24% agreement). Next, the two coders met in the presence of one of the authors, who participated in the discussion to gain a deeper understanding of the scores but did not bias any of the answers. The coders discussed the few differences in the scores and agreed a single final measure of performance for each protocol. Using two sets of coders was costly in terms of time and effort, but prevented biased data.

Given that the measures of performance and cognitive flexibility were derived from Task 2, we took several steps to mitigate the possibility of common method bias. First, to ensure the construct validity, the code structures were developed by different researchers and emphasized different aspects. The two coder groups were independent from each other, unaware of the overall aims of the project and what the other group was doing, or why. Second, the content of the code for cognitive flexibility was different from the instruction for rating performance in Task 2. The measure of cognitive flexibility was derived from a coding procedure that relied on pre-established categories. The score for performance in Task 2 was derived from two different coders' perceptions of how satisfactory the proposed solution was. Third, the coders who focused on performance were directed to focus on the final paragraph of the protocol itself, in which participants retrospectively stated their solution, whereas the coders who focused on cognitive flexibility did not examine this part of the protocol.

Results

Descriptive statistics

Table 3 presents the descriptive statistics and zero-order correlations, which reveal a high level of inter-individual heterogeneity in behavior in respect of the two tasks. The table shows that the relationship between response time and performance is negative for Task 1 and positive for Task 2. In addition, cognitive flexibility is significantly and positively correlated with processing time and performance in respect of Task 2.

Insert Table 3 about here

Hypothesis test

A panel data analysis method was employed using the 49 participants' responses and a depth of 2. A Hausman test was used to determine the efficiency equivalence between fixed and random effects (p-value = 0.98 for the full interacted model). As a result, we ran a random-effects model (not shown for the sake of brevity). Given that a Breusch Pagan test (p-value = 0.28 for the full interacted model) showed that no efficiency was gained from using a random-effects model over an ordinary linear squares (OLS) method, we opted to model our data using OLS.

Table 4 presents the results of the hierarchical moderated regressions used to test our hypotheses through a three-way interaction. In models 3–7, our dependent variable is performance in respect of each of the tasks. We standardized our variables so we could directly compare them problem by problem, and to create a cumulative performance measure for the two tasks (used in Models 1–2). The baseline model (Model 1) contains the control variables; Model 2 tests Hypothesis 1 by including the effect of cognitive flexibility. As shown, cognitive flexibility has a positive effect on performance. An increase of one unit in the cognitive flexibility score improves performance by 0.21 standard deviations (p-value = 0.10). This offers moderate support for Hypothesis 1: the higher the cognitive flexibility, the higher the performance. This moderate relationship might reflect the processes involved. Given that the default-interventionist mode assumes that Type 1 processing is the default, cognitive flexibility will be more apparent in the switch to Type 2 processing, but less so in the reversion to Type 1 processing. The default-interventionist mode also assumes that Type 2 processing acts in addition to Type 1 processing, rather than replacing it. Hence, given that Type 1 processing is always present, this result shows that cognitive flexibility is manifested mainly in the positive association between Type 2 processing and performance in respect of Task 2.

Model 3 includes the direct effects of type of task and processing times on performance. Model 4 tests Hypothesis 2 by adding a term of the moderation task x response time; the addition of this term increased the explained variance, R2, by 0.27, and gives two very different slopes for performance as a function of time for well- vs. ill-structured tasks. For the well-structured task, a higher processing time decreases performance ($\beta = -0.61$, $p = 4 \times 10^{-6}$). This result supports Hypothesis 2a: Type 1 processing is associated with higher performance in a well-structured task[6]. The opposite happens when the task is ill structured: a higher processing time increases performance ($\beta = 1.11$, 4×10^{-8}). This result supports Hypothesis 2b: Type 2 processing is associated with higher performance in an ill-structured task. It is interesting to note, as shown in Model 2, that the relationship between cognitive flexibility and performance becomes insignificant when the moderations for processing times are taken into account. This signals that the explanatory power of cognitive flexibility is in turn explained by the match between problem and processing type.

Models 5 and 6 provide the additional combination of the terms that will be included in the three-way interaction (cognitive flexibility x response time and cognitive flexibility x task); jointly, both models increase the explained variance by one percent, and the slope is not significant for either term.

Model 7 tests Hypothesis 3 through a three-way interaction term; the inclusion of this term increases the proportion of variance explained by four percent to a total of 0.36. We find support for Hypothesis 3: the higher the cognitive flexibility, the more likely the use of Type 1 processing in a well-structured task and Type 2 processing in an ill-structured task. When the problem is well structured (Task 1), the interaction between cognitive flexibility and processing time has a negative effect on performance ($\beta = -0.32$, $p < 0.1$). When the problem is ill structured (Task 2), the interaction between cognitive flexibility and processing time has a positive effect on performance ($\beta = 0.43$, $p < 0.05$). The significant three-way interaction is consistent with our theoretical arguments that propose cognitive flexibility as a moderator of the relationship between problem type and processing type.

Insert Table 4 about here
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[6] Notice that within Task 1 there are also brief phases of deliberation. These became evident when analyzing the response times for Task 1: a bimodal function emerges. The majority of the response times are low, but there are brief bursts of deliberation in a minority of trials. Consistently, during the debriefing session, many participants reported approaching Task 1 in an automatic manner, punctuated by some deliberative interventions.

Examining three-way interactions

To facilitate interpretation of the effects of the three-way-interaction model, in Figure 3 we present a simple slope coefficient for individuals with high (+1 s.d.), average, or low (-1 s.d.) cognitive flexibility. For both tasks, the vertical axis shows the performance progression as processing time increases (horizontal axis). The main performance difference between individuals with low and high cognitive flexibility in these two tasks is due to the switching accuracy provided by cognitive flexibility.

In the well-structured problem, the correctly matched processing type (Type 1 processing) leads to enhanced performance for all participants, particularly for high-cognitive-flexibility individuals. Interestingly, the converse is also true: mismatching the processing type (Type 2 processing) leads to poor performance for all participants, particularly for high-cognitive-flexibility individuals. One could say that if participants use Type 2 processing for the well-structured task (i.e. they are slow to answer), their performance consistently suffers—but this deterioration is more severe for highly cognitively flexible individuals. It appears that deliberate thinking, if inappropriately deployed, is relatively more disadvantageous for individuals with high cognitive flexibility. However, as discussed below, individuals with high cognitive flexibility are less likely to deploy the mismatched type of processing.

In the ill-structured problem, correctly matching processing type (Type 2 processing) leads to enhanced performance for all participants, but especially high-cognitive-flexibility individuals. In other words, deliberative responses from cognitively flexible individuals translate into greater increases in performance. Adopting a mismatched processing type undermines performance to the same extent for all participants, irrespective of their level of cognitive flexibility.

Insert Figure 3 about here

Post hoc analyses and robustness checks

To further verify our research findings, we conducted various additional analyses. First, in addition to the OLS regressions, we ran robust regressions via iterated re-weighted least squares. Robust regressions give qualitatively similar results to the OLS, except for one term (the interaction between cognitive flexibility and processing type), which has a weaker significance level than in the previous regression. We did not observe any other noteworthy differences in the direction or significance level of any of the findings of substantive interest. Accordingly, we have not reported the findings of these supplementary analysis here in the paper, but they are available for interested readers upon request.

Second, to corroborate the finding that higher cognitive flexibility is associated with shifting cognitive processing in response to varying task environments, we compared the groups with lower and higher cognitive flexibility in terms of their processing times (Table 5). The results suggest that individuals with low cognitive flexibility not only fail to adapt their cognitive processing strategies to varying task demands, but they also tend to use a mismatched type of processing: They tend to be slower than average in the well-structured task (their processing time is on average 0.20 standard deviations above the mean processing time on Task 1), and faster than average in the ill-structured task (they are on average 0.25 standard deviations below the mean processing time on Task 2, $p < 0.1$).

The opposite is true for individuals with high cognitive flexibility: They tend to be quicker in the well-structured task and slower in the ill-structured one. Their processing time is on average 0.33 standard deviations below the mean processing time on Task 1 and 0.38 standard deviations above the mean processing time on Task 2 ($p < 0.1$).

Insert Table 5 about here

A third additional check was a sensitivity analysis aimed at exploring the “elasticity” of our proposed model by imputing possible values of cognitive flexibility and processing times in the coefficients of our regression model, and observing the impact on performance in each task. Our results were confirmed, and we gain a better understanding of the potential cases that might arise when individuals have high or low cognitive flexibility but do not necessarily match the processing type to the type of problem. In Table 6 we split individuals into the eight different types of possible behaviors, in accordance with how they scored in comparison to the mean (i.e., higher or lower) on the dimensions of: cognitive flexibility, processing time in Task 1, and processing time in Task 2 (columns 1–3). Column 4 shows the likelihood that each of those types of behavior appears in our sample. For example, fast processing time on Task 1 and slow processing time on Task 2 is likely to happen in 14 percent of the individuals with low cognitive flexibility, but 38 percent of the individuals with high cognitive flexibility. We used the regression results obtained in Model 7 of Table 4 to predict the performance of representative individuals of each type (that is, those who have values of either one standard deviation above or below the mean in processing times for both tasks and for cognitive flexibility). The performance obtained is presented in columns 5–7 of Table 6. Significantly, Table 6 reveals that there is no deterministic association between cognitive flexibility and performance, and further confirms that the choice of processing type is not dependent on the type of task. It appears that highly flexible individuals can still either fail to switch processing modes. or use a ,mismatched processing mode—albeit with a lower likelihood. See, for example, the likelihood of failing to switch modes in row [5], showing high cognitive flexibility and fast response times (24%), or in row [8], showing high cognitive flexibility and slow response times (14%)—or, conversely, the likelihood that high cognitive flexibility individuals use the mismatched processing type (24%) in rows [5] and [7]. On the other hand, our results show that less flexible individuals can still perform well, but with a significantly lower likelihood than people with higher cognitive flexibility. When we calculate a simple weighted mean of the average performance multiplied by the likelihood that individuals behaved like each of the types, we find that the mean performance for low cognitive flexibility would be -3.87 on average, while performance for high cognitive flexibility would be +2.83. The normative solution for individuals with both high and low cognitive flexibility is to respond quickly (i.e. to use Type 1 processing) in respect of Task 1, and deliberate for longer in respect of| Task 2 (i.e. use Type 2 processing). Interestingly, when individuals from the low-cognitive-flexibility group behave as in the normative solution, their mean performance is 0.19, while the mean performance for individuals from the high-cognitive-flexibility group is 0.42. Thus, cognitive flexibility appears to be a crucial factor in individuals optimizing cognitive processing strategies in response to different task environments.

Insert Table 6 about here

Finally, one might consider cognitive flexibility nothing but a form of general intelligence, as measured by standard IQ tests—but this is not the case. We expect our cognitive flexibility measure to be positively correlated with measures of intelligence, but we do not expect this correlation to be significant. Hence, we collected data on a test commonly used as a proxy for general intelligence (Raven *et al.*, 2003); the correlation between cognitive flexibility and the score in the Raven's test is 0.2019 (sig. 0.1687).

Discussion

Our empirical analyses provide support for our three hypotheses. Cognitive flexibility has a positive impact on performance, and this positive impact appears to be effected via the matching of different types of cognitive processing in response to different task environments. Our core contribution lies in the identification of cognitive flexibility as a plausible mechanism that effects the switch between the two types of cognitive processing depending on the problem at hand. When taking into account the three-way interaction between cognitive flexibility, type of cognitive processing, and type of task, we find a positive interaction that shows that the higher the cognitive flexibility, the more likely the use of Type 1 processing in a well-structured task and Type 2 processing in an ill-structured task. On this basis, and in line with past research in strategic management (Hodgkinson and Healey, 2011; Levinthal and Rerup, 2006; Louis and Sutton, 1991) and the cognitive sciences (Evans and Stanovich, 2013; Lieberman, 2007), the concept of cognitive flexibility allows us to integrate the discussion regarding two different types of decision-making processes: one based on less-mindful, autonomous, and semi-autonomous responses, and another one based on controlled, mindful, deliberate decision-making processes. Our empirical results indicate that cognitive flexibility lies at the interface between these two processes. Indeed, it is a key adaptive mechanism among strategic decision-makers.

Our study makes three contributions. First, our results contribute to the stream of literature that identifies cognitive flexibility as a managerial capability (see, e.g. Barr and Huff, 1997; Barr *et al.*, 1992; Helfat and Peteraf, 2015; Hodgkinson, 1997; Hodgkinson and Healey, 2011; Hodgkinson and Sparrow, 2002; Louis and Sutton, 1991; Reger and Palmer, 1996; Teece, 2007; Tripsas and Gavetti, 2000; Laureiro-Martínez *et al.* 2014). We provide evidence that decisions-makers high in cognitive flexibility perform better.

More specifically, we build upon and extend Helfat and Peteraf's (2015) conceptualization of managerial 'cognitive capabilities' as the micro foundations of dynamic capabilities. We have focused on one specific micro-level capability (cognitive flexibility) that might support the emergence of a superior combinations of 'sensing-seizing-reconfiguring' capabilities. Our analysis, framed in terms of switches between Type 1 and Type 2 processing, provides evidence that the interplay of deliberate and less deliberate modes of thinking is important to understand the differential abilities of managers to face uncertainty and change. Interestingly, our result also identifies an important possible contrast between micro and macro level results. As also discussed in Helfat and Peteraf (2015), prior work at the organizational level seems to associate the reliance on semi-automatic responses (heuristics) to the ability of copying with uncertainty (Bingham, Eisenhardt and Furr, 2007). Our micro-level results seem to point in the opposite direction. We believe this kind of contrasts identifies a very promising direction of research to foster the agenda about microfoundations in strategy research. It is exactly when micro-level results do not map orderly in macro-level findings that microfoundations become a non-trivial, and rather interesting, problem which is also promising in terms of relevance. Indeed, authors like Eisenhardt *et al.* (2010) and Raes *et al.* (2011) have proposed that cognitive flexibility resides in the interaction of the top management team and middle managers, and that it is developed over time. By proposing an individual-level matching mechanism, we complement that literature and lay the foundation for future studies. Yet, a number of questions present themselves in relation to the evolution and development of cognitive flexibility as a managerial capability. Can managers manipulate the work environment to increase cognitive flexibility (Vuori and Huy, 2015)? Can we develop interventions aimed at increasing cognitive flexibility? Research so far has focused mostly on specific populations, in particular children (Diamond and Lee, 2011) or video-gamers (Colzato *et al.*, 2010). Yet, these questions are of great managerial relevance as in real organizations, whole areas of work related to strategic change as well as new product development, innovative methods such as agile product development teams (Brown, 2008; Gruber *et al.*, 2012) or innovation contests (Boudreau, Lacetera, and Lakhani, 2011) are challenging established patterns of specialization, and exposing people to an increasing range of very different problems in cross-functional teams. These new, fluid organizational setups require strategic decision-makers to continuously pay attention to problems of many different types. As such practices increase, the discussion about cognitive flexibility, and how it is affected by organizational processes and structures, will become even more important. Our study intends to provide solid micro foundations to this discussion, on the basis of a clear understanding of what cognitive flexibility is at the individual level. For example, our findings are important because they corroborate the idea that deliberation is not necessarily the superior problem solving strategy to adopt at all times. Indeed, we find no deterministic association between flexibility and performance. In our samples, even highly flexible individuals mismatch processing type, though with a lower likelihood. Our results show that people with low cognitive flexibility can still do well, but with a significantly lower likelihood than people with higher cognitive flexibility. Other factors, psychological or environmental, may play a role. For example, Elsbach and Barr (1999) found that the type of protocol used to solve complex problems is contingent on mood: individuals in moderately negative moods are more likely to follow step-by-step procedures. Bledow *et al.* (2013) found a positive relationship between cognitive flexibility and positive affect. How can positive affect and other, more general emotions that are experienced in the work environment impact cognitive flexibility? Are both types of processing equally susceptible to mood or fatigue conditions?

As a second contribution, our results add to prior work on inertia and flexibility. In particular, by focusing on an individual-level ability—cognitive flexibility—that can explain differences in adaptive decision-making, we provide a more precise discussion about what makes individuals decision makers more or less flexible and open to change. Prior work has identified the excessive stability of mental representations as the dominant cause of inertia—hence the prevalence of discussion about flexibility and adaptation (Barr *et al.*, 1992; Gavetti, 2005; Gavetti and Levinthal, 2000; Grewal and Tansuhaj, 2001; Hodgkinson, 1997; Levinthal and March, 1993; Nadkarni and Narayanan, 2007; Reger and Palmer, 1996; Worren *et al.*, 2002). Our findings provide a more nuanced definition of flexibility, and the specific mechanisms underpinning it: identifying the different elements of a situation, reflecting on them, and choosing an appropriate behavior. More specifically, the ability of recognizing and valuing diversity in viewpoints, opinions and preference enable decision makers, depending on the situation, to proceed with a thorough analysis of all elements, or selecting a few key aspects to guide behavior. The former approach manifests itself as a slow-down, think-twice approach. The latter using rules of thumb. On this basis, we argue that making a key strategic decision depends on cognitive flexibility. Our study represents a useful way of considering flexibility and inertia, but a very parsimonious one. Our conclusions are limited by the simplicity of our operationalization in terms of ill- vs. well-structured problems. Moreover, while each task could involve more or less Type 1 or Type 2 processing, we simply compared the average involvement of each type of thinking on each task to ascertain the predominant type of processing being used. For the ill-structured task, future studies could complement the use of response times with analyses of verbalization pacing, since Type 2 processing is more likely to result in multiple pauses than Type 1 processing. In the well-structured task, techniques such as EEG or fMRI could be used to complement behavioral data.

As a third contribution, we believe our results contribute to move the discussion about managerial cognition "beyond the static comparison of individuals' cognitive maps, still commonplace in strategy process research (e.g. Hodgkinson and Johnson, 1994), to a deeper understanding of what lies behind the actions of strategists as they engage with the various practices deployed in their praxis" (Hodgkinson and Clarke, 2007, p. 251). While we present individual-level evidence, we believe that our results illustrate the microfoundations of the organizational ability to change and adapt. We focus on the initiators of these processes: those who can trigger change by recognizing that a new "problem" has to be approached in a different way. Of course, in real life, the actual change process also involves an organizational dimension, which we do not observe in our setting. Yet, there are also advantages in focusing on individuals. For example, the processes we observe relate to March's (1991) discussion about organizational learning. For March, there are two types of code learners: fast and slow. In his analysis, fast learners are those who converge rapidly toward the organizational code, yet contribute little novelty to it. Slow learners are those who converge slowly to the organizational code, and in so doing enrich it through their persistent diversity. They deliberate more, explore more options, and maintain heterogeneity in the organizational code. In so doing, by making mistakes, slow learners learn less from the code, but keep exploration going at the organizational level, hence generating more knowledge for the organization, which benefits the fast learners. We might speculate that March's slow learners are individuals who rely more on Type 2 processes: maintaining diversity, they contribute more to the code, but might also make bigger mistakes. Conversely, March's fast learners are individuals who rely more on Type 1 processes: they have faster responses because they rely more on the existing organizational code, but contribute less to it. We are not claiming to observe the aggregation from individual beliefs to organizational code, but we do suggest that the individual processes observed in this paper give traction to one March's most important results.

Finally, prior research has identified the importance of cognitive flexibility for strategic change (Hodgkinson, 1997; Hodgkinson and Clarke, 2007; Louis and Sutton, 1991; Raes *et al.*, 2011), less attention has been devoted to the analysis of the specific mechanism underpinning the relationship between cognitive flexibility and performance, i.e. the identification of the key aspects of the problem and the reflection upon their possible connections and effects. This lack of attention is probably due to the many tradeoffs and limitations faced by researchers empirically studying this topic. For example, they have to choose the type of approach (daily strategic decisions vs. lab studies), the profile of participants (experienced vs. inexperienced), and the design of the study (between-task vs. within-task). Here, we opted for a lab study—which, despite its rigor, comes with limitations. For example, while field research is based on actual strategic decisions and its ecological validity is evident, it lacks the rigor of a lab study (Maule and Hodgkinson, 2002). Importantly, though, both approaches have yielded rather similar findings (Hodgkinson *et al.*, 1999; Hodgkinson *et al.*, 2002; Maule and Hodgkinson, 2002). In this study, to achieve comparability, we purposefully designed tasks that exclude the role of task- or environment-specific expertise. Our research design captures the nature and structure of many of the tasks that decision makers face every day. However, not all types of task structures are represented in our design setting. We do not consider tasks that are repetitive but involve no uncertainty, or problems that are solved unconsciously, or those that are better solved in a parallel, rather than sequential manner. While switching tasks sequentially requires cognitive flexibility, multitasking relies on divided attention that allows individuals to perform tasks in parallel (Judd, 2013). Since multitasking involves constantly and rapidly shifting mental sets between tasks (Monsell, 2003), it can also be related to cognitive flexibility, and future studies could explore settings in which two problems must be solved at precisely the same time. Extending this paper's methods, participants could read the ill-structured problem, and then solve it while also solving the well-structured problem. Our empirical design serves as a baseline upon which future studies can add complexity to the setting by, for example, reducing cognitive load through decision-making support systems and studying how this might help some individuals more than others.

We also recognize that our conception of cognitive inertia—that is, the inability to correctly match processing strategies to different problems—is limited. It might be that one does indeed match the correct processing, but change is impeded by some other factor that we do not capture in our setting—such as, for example, strong emotional attachment. We see this study as a baseline to build upon.

In conclusion, our study shows that cognitive flexibility is an important antecedent of effective individual decision-making when faced with different types of problems. In doing so, it connects ongoing work in managerial cognition with that in cognitive sciences, making a micro-founded and empirically operationalizable link between the literatures on cognition and strategic decision-making. Such a link is crucial to extending and deepening our understanding of the microfoundations of strategy research.

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Figures and tables

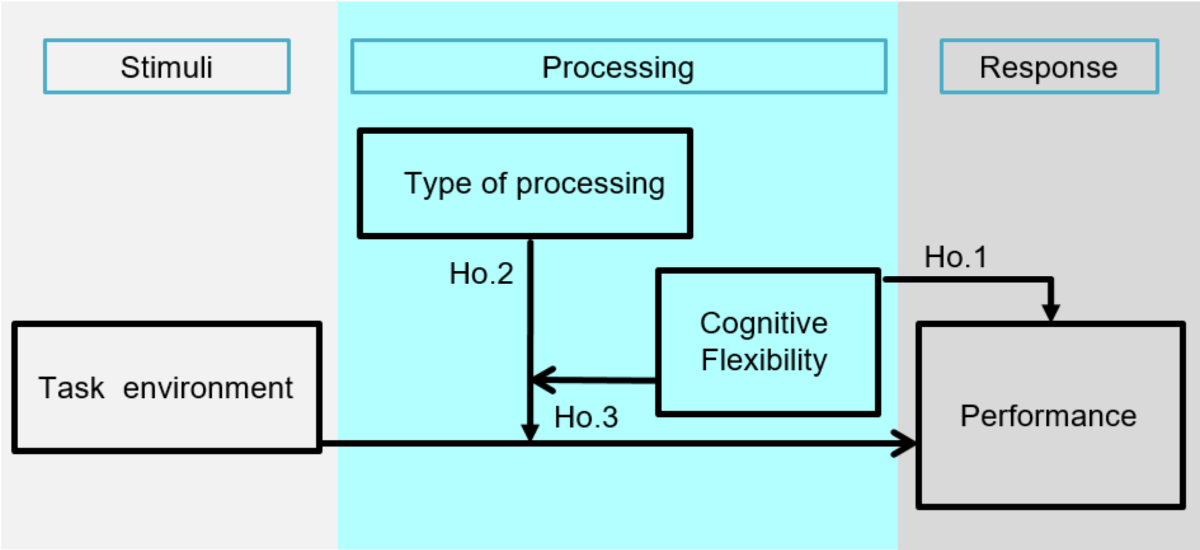

Figure 1: A model of cognitive flexibility and adaptive decision-making

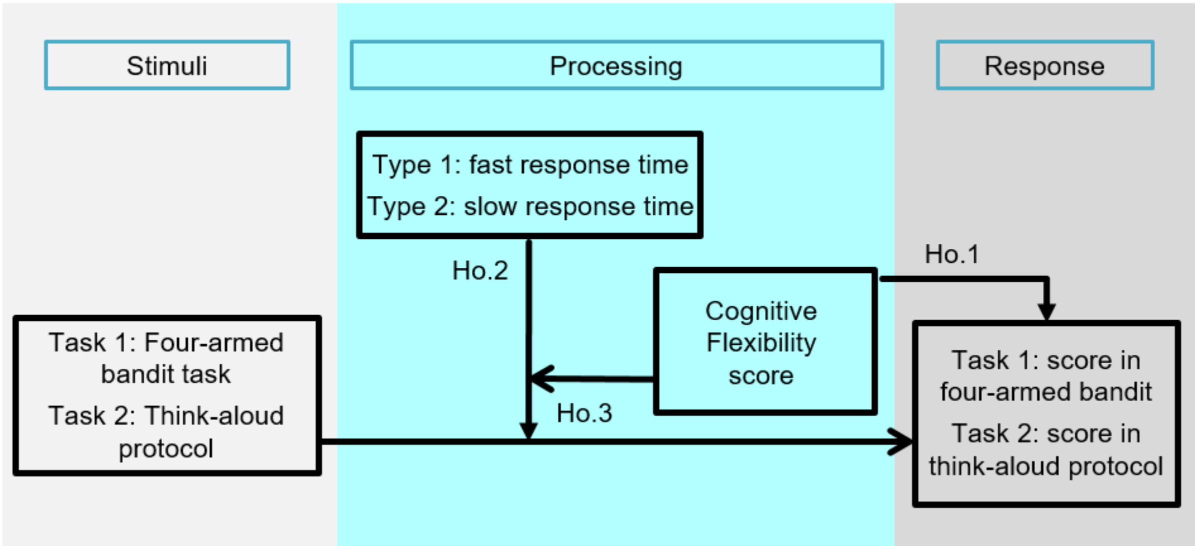

Figure 2: Model operationalization

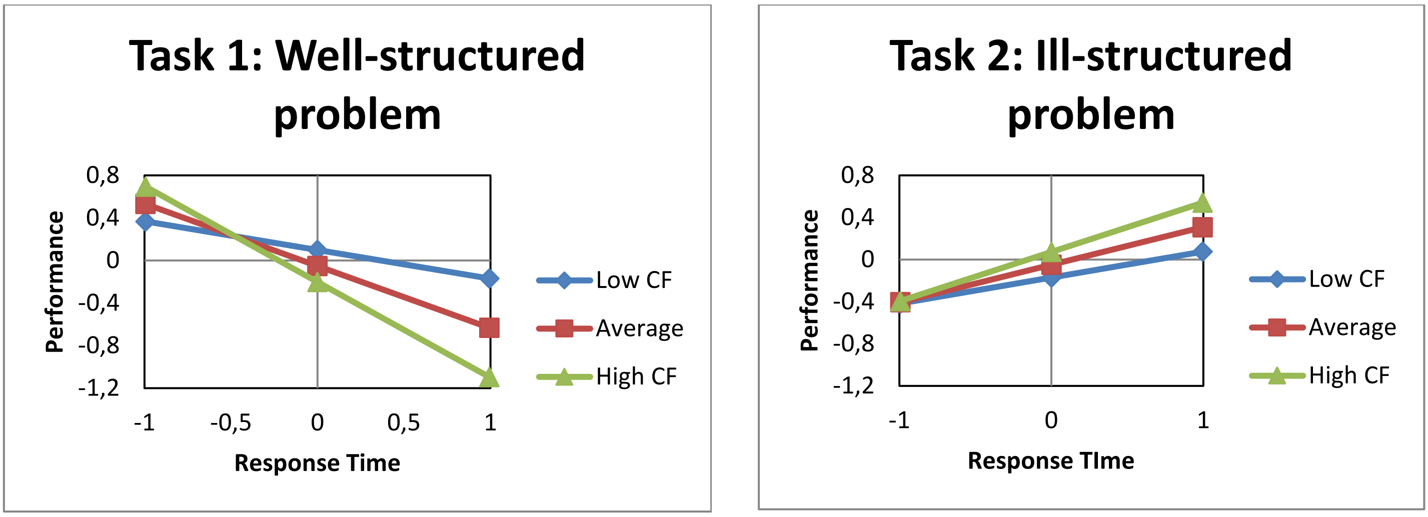

Figure 3: Plotting significant three-way interactions. The left panel of Figure 3 shows that for the well-structured task, a decrease of 1 s.d. in processing time (being 0.48 minutes faster) increases performance by 0.27 s.d. (159 points in the "four-armed bandit" task) for individuals with low cognitive flexibility and by 0.90 s.d. (532 points) for individuals with high cognitive flexibility. In a well-structured task, an individual with high cognitive flexibility will perform worse than one with low cognitive flexibility as response time increases. In the case of ill-structured tasks (the right panel of Figure 3), a decrease of 1 s.d. in processing time (equivalent to 10.8 minutes) decreases the performance of low-cognitive-flexibility individuals by 0.25 s.d. (that is, 0.26 points in the think-aloud protocol score) and by 0.47 s.d. (0.50 points) for high cognitive flexibility individuals—that is, a mismatch between task and processing type diminishes performance almost equally for all participants. On the other hand, an increase of 1 s.d. in processing time (equivalent to 10.8 minutes) will greatly favor high-cognitive-flexibility participants.

Table 1: Types of cognitive processes

Type 1 processes	Type 2 processes
Defining features	
Automatic Autonomous Do not require working memory	Controlled Not autonomous Require working memory
Typical correlates	
Fast response High capacity and parallel processing Unconscious Biased responses Contextualized Automatic and associative Experience-based decision-making Independent of cognitive ability	Slow response Capacity limited and serial processing Conscious Normative responses Abstract Controlled and rule-based Consequential decision-making Correlated with cognitive ability
Also associated with:	
Similar to animal cognition, evolved early Learning by association Basic emotions	Distinctively human, evolved late Learning by deliberation Complex emotions

Adapted from: Evans and Stanovich (2013), Kahneman (2011), Lieberman (2007), Satpute and Lieberman (2006)

Table 2: Code for cognitive flexibility

Analytical categories	Subcategories	Operationalization
Key problem elements' identification	Identification of different problem elements and views	The statement includes observations, questions, and issues regarding alternative points of view of the problem. The statement can include discrepant information. In addition, the statement demonstrates awareness of the existence of alternative takes on the situation (+1).
	Identification of different communication possibilities	The statement demonstrates awareness of alternative communication possibilities for dealing with, acquiring, or transmitting information to/from others (+1). If automatic or immediate communication is assumed, a point is deducted (-1).
	Attempts at developing knowledge about other problem elements	The statement refers to gathering additional information that belongs to other individuals' views on the problem (+1).
	Attempts at developing knowledge about the identity of other individuals	The statement refers to gathering additional information that will help understand other individuals. The statement can demonstrate awareness that additional knowledge is needed to obtain a more complete understanding of the identity of other individuals (+1).
Reflective perspective	Recognition of differences in the knowledge/ interpretations of others	The statement shows reflection about the differences between self and other individuals' knowledge and interpretation of the situation (+1).
	Recognition of difficulties for identification	The statement demonstrates awareness about the difficulties involved in putting oneself into someone else's shoes (+1).
	Attempts at developing dialogical practices	The statement contemplates efforts towards establishing a dialogue (+1).
	Stereotyping (generalization) and prejudice errors (attitudes)	The statement applies stereotypes and prejudices to the individuals or to the causal relations involved in the situation (-1).

Table 3: Descriptive statistics and zero-order correlations

Variable	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Age	40.4	6.74	1.00							
2. Gender	0.18	0.39	−0.25	1.00						
3. Cognitive flexibility (CF)	2.18	4.53	0.10	−0.34	1.00					
4. CF binary	0.46	0.51	0.12	−0.31	0.88	1.00				
5. Response time 1	7.14	0.48	−0.04	0.22	−0.16	−0.33	1.00			
6. Performance task 1	18,069	594	−0.05	0.06	0.02	0.28	−0.59	1.00		
7. Response time 2	13.3	10.8	−0.18	−0.19	0.45	0.34	−0.21	0.03	1.00	
8. Performance task 2	5.98	1.07	0.00	−0.08	0.33	0.36	−0.05	0.11	0.50	1.00

Note: Absolute value of correlations greater than 0.28 statistically significant at $p < 0.05$ for two-tailed tests.

Table 4: Regression models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Dependent variable	Cumulative performance			Task-related performance			
Control variables							
Age	−0.10[0.87] (0.58)	0.24[0.69] (0.60)	0.04[0.72] (0.11)	−0.04[0.69] (0.09)	−0.04[0.70] (0.09)	−0.03[0.73] (0.09)	−0.01[0.94] (0.09)
Gender	0.05[0.82] (0.23)	0.06[0.80] (0.22)	0.13[0.65] (0.29)	0.33[0.18] (0.25)	0.33[0.19] (0.25)	0.33[0.19] (0.25)	0.23[0.35] (0.25)
Independent Variables							
Cognitive flexibility (CF)		0.09[0.10] (0.05)	0.21[0.06] (0.11)	0.05[0.59] (0.10)	0.05[0.59] (0.10)	−0.05[0.71] (0.13)	−0.15[0.27] (0.14)
Task structure			−0.00[1.00] (0.20)	−0.00[1.00] (0.17)	−0.01[0.98] (0.18)	0.01[0.94] (0.18)	0.00[0.99] (0.18)
Response time (RT)			−0.08[0.42] (0.10)	−0.61[4 x 10^{-6}] (0.12)	−0.61[5 x 10^{-6}] (0.13)	−0.62[4 x 10^{-6}] (0.13)	−0.59[1 x 10^{-5}] (0.13)
Interactions							
RT x Task				1.11[4 x 10^{-8}] (0.19)	1.11[2 x 10^{-7}] (0.20)	1.09[4 x 10^{-7}] (0.20)	0.94[2 x 10^{-5}] (0.21)
CF x RT					0.01[0.91] (0.09)	−0.02[0.80] (0.09)	−0.32[0.05] (0.16)
CF x Task						0.23[0.25] (0.20)	0.27[0.16] (0.19)
CF x RT x Task							0.43[0.03] (0.20)
Intercept	0.02[0.94] (0.24)	−0.23[0.41] (0.28)	−0.02[0.88] (0.15)	−0.06[0.64] (0.13)	−0.06[0.66] (0.13)	−0.06[0.62] (0.13)	−0.09[0.47] (0.13)
Observations	49	49	98	98	98	98	98
Number of parameters	2	3	5	6	7	8	9
R^2	0.00	0.06	0.04	0.31	0.31	0.32	0.36
ΔR^2	-	0.06	-	0.27	0.00	0.01	0.04
Adjusted R^2	−0.04	−0.00	−0.01	0.27	0.26	0.26	0.29
F statistic	1.07	1.20	0.78	6.92	5.87	5.32	5.46
Maximum VIF	0.03	0.98	1.20	2.28	2.58	2.59	6.11

Note: p-values in square brackets (two-tailed); standard errors in parentheses.

Table 5: Cognitive flexibility and problem-solving response time

Response time		Cognitive flexibility		*p*-value
		low	high	
Task	1	0.20	−0.33	0.08
	2	−0.25	0.38	0.09

Table 5 note: Values show standard deviations, above and below the mean processing times for each task for groups of low and high cognitive flexibility.

Table 6: Performance by cognitive flexibility and processing types

[1]	[2]	[3]	[4]	[5]	[6]	[7]	
Cognitive flexibility	Response time		Likelihood of behavior (%)	Performance			
	Task 1	Task 2		Task 1	Task 2	Mean	Row:
Low	fast	fast	36	0.25	−0.30	−0.02	[1]
		slow	14	0.25	0.13	0.19	[2]
	slow	fast	46	−0.36	−0.30	−0.33	[3]
		slow	4	−0.36	0.13	−0.12	[4]
High	fast	fast	24	0.73	−0.64	0.04	[5]
		slow	38	0.73	0.40	0.57	[6]
	slow	fast	24	−0.92	−0.64	−0.78	[7]
		slow	14	−0.92	0.40	−0.26	[8]

Table 6 note: This table splits the sample into different categories resulting from different levels in cognitive flexibility and response time in each of the two tasks. For example, row [6] shows the share of participants (column [4]) with high cognitive flexibility whose processing time is fast in task 1 (column [2]) and slow in task 2 (column [3]). The likelihood of observing such behavior among high-cognitive-flexibility participants is 38 percent (row [6], column [4]). Their expected mean performance in both tasks (row [6], column [7]) is +0.57. In contrast, the likelihood of observing such behavior among participants with low cognitive flexibility is 14 percent (row [2], column [4]). Their expected mean performance in both tasks (row [2], column [7]) is +0.19.