The Value of Knowledge: How Nth Best Solutions Affect Organizational Search

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Abstract
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State of the Art
While neoclassical economic theories are theories about the optimal (or 1st best) solution, management and organization theories are, more or less explicitly, theories about the nth best solution. This idea is perhaps most explicit in Levinthal’s (1997) theory of adaptation in rugged landscapes: organizations will tend to converge only to a local peak (or an nth best solution) and fail to find the global peak (i.e., the 1st best solution). The notion that the current best solution is most likely not the optimal solution is also also implicit in other theories. Take for example the literature on practice transfer: Even when we call a solution a “best practice” (e.g., Spender & Grant, 1996; Szulanski, 1996) it is often not literally the 1st best solution but, most of the times, only the best currently known alternative, i.e., at best, a 2nd best solution.

Research Gap
Even though most organizational decisions are done on the basis of knowledge of nth best solutions, our models of search and learning often focus on the case where agents are endowed with knowledge of the 1st best solution (e.g., Ghemawat & Levinthal, 2008; Rivkin, 2000). If an agent has access to the 1st best solution, then the best strategy for future action would be to always adopt that solution, i.e., to not search for a better solution. However, when dealing with nth best solutions, the optimal search strategy is far from obvious. For example, if
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Keywords: knowledge, decision-making, search, exploration, exploitation
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ABSTRACT

Different theories in management point to the idea that organizations often fail to adopt optimal (or 1st best) solutions and instead end up adopting only n-th best solutions. In this paper, we examine whether variations in knowledge about n-th best solutions affect the search strategies of human agents and, in turn, their performance. We find that when agents know that the current solution is only an n-th best solution, they are more likely to exploit their knowledge and in turn achieve a better performance. However, we also find that agents are more likely to break off exploitation of the current solution when they do not know whether that solution is the optimal, or only an n-th best solution. Finally, our results also seek to contribute to our understanding of why unknowledgeable agents may sometimes end up finding better solutions than agents endowed with knowledge about second best solutions.

Keywords: knowledge, decision-making, search, exploration, exploitation
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BEST SOLUTIONS AFFECTS ORGANIZATIONAL SEARCH

While neoclassical economic theories are theories about the optimal (or 1st best) solution, management and organization theories are, more or less explicitly, theories about the 2nd best, but in many cases, only the n th best solution. This notion is perhaps best reflected in Levinthal’s (1997) theory of adaptation on rugged landscapes: Most organizations will fail to find the global peak (or the optimal solution) and instead converge only to a local peak (or an n th best solution).

The idea that the current solution is most likely not the optimal solution is also implicit in other theories, such as theories about technological progress (Butler, 1988), dominant designs and standards (Anderson & Tushman, 1990; Rosenkopf & Tushman, 1994), benchmarking (Drew, 1997) or practice transfer (Spender & Grant, 1996; Szulanski, 1996). Take for example the literature on practice transfer: Even when we call a solution a “best practice” (Spender & Grant, 1996; Szulanski, 1996) it is often not literally the 1st best solution but, most of the times, only the best currently known alternative, i.e., at best, a 2nd best solution. Yet, confusing the optimal solution with an n th best solution can have important implications for search and performance.

Other studies have looked at the case in which agents are endowed with knowledge of optimal solutions (e.g., Ghemawat & Levinthal, 2000; Rivkin, 2000). In our study, however, we are interested in examining whether variations in knowledge about n th best solutions affect agents’ search and learning processes and, in turn, their performance. Obviously, when agents have the means to correctly identify and access the optimal solution, their best strategy is to implement it, i.e., to not learn about the value of other solutions. However, when all agents know is that their current solution clears a performance target, but not whether it is the
optimal, or an n\textsuperscript{th} best solution, determining the best search strategy is far from obvious. For example, do agents tend to adopt their current solutions, or do they tend to incur the costs of exploration in order to implement a better solution that might not exist? Alternatively, if agents have reason to believe that their current solution is not the optimal, but only an n\textsuperscript{th} best solution, will they exploit their current knowledge or will they seek to implement a better solution? Finally, what do these different strategies mean for organizational performance?

We tap into these questions by conducting two separate experiments with human subjects, based on the n-armed bandit model (e.g., Sutton & Barto, 1998). In a bandit framework, the payoffs of the different solutions are initially unknown and can only be learned through experience, i.e., agents must choose a particular solution in order to learn about its payoff. Accordingly, agents have to decide whether to exploit solutions with a known payoff, or to explore unknown solutions. We find ample evidence of satisficing behavior, especially when subjects know that the current solution is not an optimal solution (e.g., if the performance target is 0, knowledge like, “Solution X has a payoff of 2.8 and is the 2\textsuperscript{nd} best solution”). However, we also find that when subjects do not know whether the current solution is the optimal, or only an n\textsuperscript{th} best solution (e.g., knowledge like, “Solution X has a payoff of 2.8”), they will tend to explore the value of other solutions, even if this strategy does not lead to a higher performance.

These results have important implications for different streams of literature. First, from a behavioral perspective on decision-making and learning (e.g., Cyert and March, 1963; March, 1991; Simon, 1947), most organizational choices are made only on the basis of some knowledge about existing performance targets and the value of available alternatives. Yet, our results indicate that knowledge of what solutions clear the performance target does not always mean that agents will exploit those solutions and achieve a better performance. Second, our findings seek to extend theoretical discussions stemming from the evolutionary
(Nelson & Winter, 1982) and knowledge-based (e.g., Grant, 1996a; Kogut & Zander, 1992; Szulanski, 1996) views of the firm on how organizations make use of their knowledge resources. We find that individuals maintain a strong preference for these knowledge endowments, even after being exposed to the low-performance that comes with its use. In this sense, our results may also help understand why sometimes industry newcomers end up finding better solutions than actors with some pre-entry knowledge (e.g., Carnahan et al., working paper). Finally, our findings also address recent appeals of organizational theory to contrast the predictions of our formal models of search with findings from experimental research (e.g., Puranam et al., 2015). We contribute to this by providing experimental evidence of the effects of knowledge about n\textsuperscript{th} best solutions on agent search.

THEORETICAL BACKGROUND

Even though adaptation tends to occur through a process of cognitively rich, agentic behavior (Aggarwal, Posen, Workiewicz, 2016), complex systems like organizations have been known to constantly fall back on “good-enough”, or suboptimal solutions (e.g., Carroll & Harrison, 1994; Gavetti, Levinthal, & Rivkin, 2005; Herriot et al., 1985; Holland, 1975; Kauffman, 1993; Levinthal, 1997; Levinthal & March, 1981). For example, Levinthal’s (1997) model of search on rugged landscapes captures this phenomenon well. By integrating March and Simon’s (1958) concept of “neighborhood search” in the form of local “hill-climbing”, the model shows that organizations often fail to find the global peak, or optimal solution and instead converge only to a local peak, or an n\textsuperscript{th} best solution. Other studies, which have looked at for example the power of analogy in the context of strategic decisions (Gavetti, Levinthal, & Rivkin, 2005) have also found similar results, suggesting that not even the best strategic representations allow organizations to find optimal solutions.
At the same time, models of search in turbulent environments (e.g., Posen and Levinthal’s, 2011) have also suggested that besides being hard to find, optimal solutions also run the risk of quickly turning obsolete. This last notion, in particular, is implicit in several streams of literature. Take, for example, discussions on technological progress (Butler, 1988), dominant designs and standards (Anderson & Tushman, 1990; Rosenkopf & Tushman, 1994), or benchmarking and practice transfer (e.g., Drew, 1997; Spender & Grant, 1996; Szulanski, 1996). In these and other theories, the underlying assumption is that the current solution is never the optimal solution. However, we argue that confusing knowledge of n-th best solutions with knowledge about the optimal solution can have important implications for search and, consequently, performance.

Knowledge of Performance Targets

Performance targets, such as aspiration levels, benchmarks, indexes or other reference groups (Greve, 1998; Smith & Chae, 2017) allow boundedly rational agents to determine future decisions and desired outcomes (Bromiley & Harris, 2014; Greve, 1998) by helping them balance the exploration vs. exploitation trade-off (Cyert and March, 1963; March and Simon, 1958). For example, according to classic feedback theory (Greve, 2003; Greve, 1998; Scott & Davis, 2007) if agents have expectations about the average payoff of available solutions in a given industry and their current solution falls below this industry average, they may search until they find a solution that returns an above-average payoff.

Further contributions to this theory have also suggested that when performance falls below the target, risk-taking and search are mostly contingent on a firm’s resource endowments (Audia & Greve, 2006, Levinthal, 1991), whereas when performance clears the target, further increases in performance will only tend to decrease risk-taking behavior (Bromiley et al. 2001; Nickel & Rodriguez). Finally, there is also evidence suggesting that
enhancement motives can lead organizations to actually select different aspirational levels (Moliterno, Beck, Beckman, & Meyer, 2014), or reference groups (Smith & Chae, 2017) as a function of their past experience, including comparing themselves to poorly performing organizations (Audia et al, 2015).

In this paper, however, we seek to understand how different types of knowledge about the value of existing solutions affects agent’s search. In particular, we look at situations in which agents know that a particular solution clears the performance target, but not whether it is the optimal solution and at situations in which agents have reason to believe that the current solution is not the optimal solution.

Knowledge of Solutions

In organizations, agents often deal with performance knowledge in the form of sales revenues, customer loyalty and retention reports, rankings and ratings, or size of gross margins, among other measures. From a behavioral perspective, knowledge about the performance of different solutions is important because it allows agents to make informed and better choices regarding future action (e.g., Cyert & March, 1963; March, 1991; Simon, 1947).

On the one hand, knowledge that the payoff of a particular solution falls below the target automatically increases the value of exploration, and research has actually suggests that organizations in these circumstances tend to avoid these solutions and to focus instead on learning about the value of other solutions (Audia & Greve, 2006; Greve, 2003; Greve, 1998; Scott & Davis, 2007). This view of the positive value of negative knowledge endowments is also sustained by the recent emergence of conferences dedicated to the topic of failure (e.g., FailCon), discussions about the value of null patents (e.g., Seymore, 2011), or even the
establishment of academic journals dedicated to the publication of negative results (e.g., Journal of Negative Results in BioMedicine).

However, when agents are endowed with knowledge that the current solution is already above a set performance target (i.e., when they have positive knowledge), Simon’s (1947) notion of satisficing behavior predicts that agents will inhibit search in favor of adopting the current solution, which will in turn allow them to achieve a better performance than if they were to keep searching for the optimal solution, given the opportunity costs involved. The notion that positive knowledge is a crucial organizational resource, however, is not only found in classic organizational theory, but is also embedded in stories of success (Mohr & Spekman, 1994), or “industry recipes” (Spender, 1989), in popular management, or in the concept of “best practices” (e.g., Christmann, 2000; Szulanski, 1996), and the power of analogy (Gavetti, Levinthal & Rivkin 2004; Gavetti & Rivkin 2005), in strategic management research.

While it might be compelling to assume that knowledge always has a positive value for search, some studies have shown that this is not always the case. For example, Haas and Hansen (2005) argue that utilizing knowledge to complete sales bids for consulting projects can actually hurt performance. Similarly, Henderson and Clark (1990) posit that prior knowledge may blind decision-making and that it may “not only not be useful, but may actually handicap the firm” (p.13). In these and other related studies, however, the definition of knowledge is less restrictive than in our study. Indeed, many studies face the challenge of measuring knowledge accurately. As a result, it is not surprising that knowledge can have negative implications for organizational decision-making if it can also imply that agents are endowed with incorrect or outdated beliefs. In our study, however, we are interested in positive knowledge endowments that are always correct and never misleading, erroneous, or outdated.
What is more, we focus on positive knowledge endowments because we wish to test scenarios in which agents must decide between exploiting existing knowledge or look for a better solution, as opposed to situations in which the best strategy is simply to not exploit (negative knowledge) or to always exploit (knowledge about the optimal solution). Furthermore, studies that look at knowledge utilization from an experimental perspective have not yet fully addressed the conditions under which human agents switch between exploration and exploitation (Puranam et al., 2015). Whereas some studies have shown the rate of switching between solutions decreases as a function of experience (Lea et al, 2011; Steyvers et al, 2009), we still do not know how knowledge about solutions with an above-target payoff affects this trade-off. While some of our models of search and learning still focus on the case where agents are already endowed with knowledge of optimal solutions (e.g., Ghemawat & Levinthal, 2008; Rivkin, 2000), we still do not know how real world agents search when they only possess knowledge about an $n^{th}$ best solution.

**METHOD**

We employ two experiments in order to investigate how individuals approach search when they are endowed with positive knowledge about $n^{th}$ best solutions. Even though experiments are known to mitigate the endogeneity issues that are typically raised in the management and organizational literature (e.g., Highhouse, 2009), they are also known to suffer from validity concerns. A question that is frequently raised by researchers is the extent to which effects found in the laboratory are still observable in the real world. In our experiments, we address these external validity issues by taking two measures: First, we depart from the traditional experimental population of university students and deliberately broaden the demographic spectrum of our sample by recruiting subjects from Amazon Mechanical Turk; a platform which has been used frequently in the past for experimental research (e.g., Eriksson &
Simpson, 2010; Mason & Suri, 2012; Paolacci, Chandler, and Ipeirotis, 2010). Second, we devise a sufficiently abstract task (in the vein of Billinger, Stieglitz & Schumacher, 2014, 2016), with the goal of capturing the most basic mechanisms of knowledge utilization in strategic decision-making.

Yet another concern of experimental research is the extent to which it minimizes measurement error, or the effects of confounding variables. In order to address these internal validity issues, we design an experimental task where participants may only reach an above-average performance (i.e., a better performance than by random choice) by utilizing the task-specific knowledge that we give them, therefore guaranteeing that our final results are not contaminated by external sources of knowledge. At the same time, demand effects, as in the case of social desirability (e.g., Fisher, 1993; Nederhof, 1985) are also controlled for, given that the entire experiment is conducted remotely and without the presence of a researcher.

Furthermore, we rule out the hypothesis that subjects may not be making optimal use of their knowledge resources because they have limited cognitive capacity to recall the provided information, or their past choices. To this end, we display relevant information throughout the tasks, such as the treatment information, the payoff of prior choices, or the number of times a subject made a particular choice. What is more, we rule out any order effects that might arise from the use of the same payoffs, in a within-subjects design, by utilizing scaled versions of these values across the different experimental tasks. Finally, we also control for the possibility that knowledge may become obsolete or misleading, given that we always treat our subjects with accurate and unbiased knowledge.

**The Experiments: General Description**

Both experiments follow a within-subjects design, with random assignment to treatment- and control-group. The underlying task in both experiments is a simple problem of balancing
exploration (trying out unexplored solutions) and exploitation (choosing solutions with a known payoff). In particular, subjects are asked to make two choices between five solutions with different payoffs, while holding different types of knowledge about the 2\textsuperscript{nd} best solution.

Before the experimental tasks take place, however, we ask our subjects to read a set of instructions about the choices they are about to make, and to answer a series of interpretation questions. Here, a rule is put in place to stop participants from progressing (and hence, from reaching our final sample), in case at least one of these questions is incorrectly answered.\textsuperscript{1} Beyond a fixed participation fee, the subjects’ incentives are directly tied to the payoff of their choices\textsuperscript{2}.

Moreover, after completing each experimental task, subjects are asked to explain the strategies behind their choices. Finally, we ask subjects whether they wished to fill in a survey, in exchange for some extra payment, which was comprised of different scales and demographic data that allowed us to investigate how they approached the choice problem.

\textbf{Experiment 1 – Search with Full Knowledge about the 2\textsuperscript{nd} Best Solution}

Experiment 1 was designed to test whether search is inhibited when the current solution is above a certain performance target, or aspirational level, but is not the optimal (or 1\textsuperscript{st} best) solution

\textbf{Control-group.} We ask subjects in the control-group of Experiment 1 to make two consecutive choices \((t_1 + t_2)\) between five solutions with unknown payoffs (e.g., \([-6, -4, 0, 1.2, 8.8]\)). Before making these choices, however, we provided participants with knowledge about a performance target, in the form of the average payoff of all five solutions (e.g., \textit{“The average value of solutions is 0”}).

\textsuperscript{1} Participants were given the choice to re-read the instructions and answer these questions again, in case did not answer them correctly.

\textsuperscript{2} Incentives ranged from 0.5$ to 0.6$ and were determined on the basis of the average hourly income of Amazon Mechanical Turk workers and on the time taken to complete each experiment in several pre-tests.
Since subjects cannot make any reasonable assumptions about the value of any particular solution, they may only use this knowledge to formulate a meaningful strategy in $t_2$. In particular, the best strategy to approach search in $t_2$ is a function of the knowledge obtained from exploring an unknown solution in $t_1$: if the payoff of this initial solution is below the performance target (i.e., -6, or -4), then the optimal strategy is to explore again in $t_2$, given that the expected value of exploration will be higher than the expected value of exploitation. Conversely, if the value of the solution explored in $t_1$ is above the performance target (i.e., 1.2, or 8.8), then the optimal strategy for $t_2$ is to exploit that same solution.

When employed correctly, the optimal strategy of the control-group has an expected value of 2.5.

**Treatment-group.** We ask subjects in the treatment-group to perform a similar task to that of the control-group, with the exception that, in the treatment-group, we endow subjects with two additional pieces of knowledge: we tell them which solution is the 2nd best solution and we reveal that its payoff is above the performance target (e.g., “The average value of solutions is 0”; “Solution 3 is the second best solution and has a payoff of 1.2”).

Notice, however, that because subjects do not know the payoff of any other solution, they may choose to approach search in four different ways: they may take this knowledge as positive knowledge (i.e., they may accept that the n$^{th}$ best solution “works”, or is “good enough”) and, therefore exploit it in $t_1$ and $t_2$ (a strategy with an expected value of 2.4); they may take this knowledge as negative knowledge (i.e., they may decided that the n$^{th}$ best solution “does not work”, or is “not good enough”) and explore in $t_1$ and $t_2$ (with an expected value of -0.6); they may use this knowledge to guarantee an above-average payoff in $t_1$ and explore an unknown solution in $t_2$ (a strategy with an expected value of 0.9); or, they may use this knowledge to explore an unknown solution in $t_1$, while keeping the above-target solution
as a fallback for $t_2$, in case they do not find a solution with a higher payoff in $t_1$ (the optimal search strategy, with an expected value of 2.8).

**Sample.** We obtained a sample of 478 US Mechanical Turk Workers, between the ages of 18 and 69 years old ($M = 35.9$, $SD = 11.1$). The majority of respondents (57.9%) were female, and 71.5% of the total sample reported that they had participated in the study to earn some additional money, whereas 13.4% revealed that taking Mechanical Turk “hits” represented their primary source of income. Participants also reported an average of three years of higher education studies by the time of the experiment.

**Results.** We start by looking at the overall performance (i.e., $t_1 + t_2$) of the two experimental conditions (Figure 1) and find that knowledge about the 2$^{nd}$ best solution leads to a better performance ($M_{Treatment} = 2.03$, $SD = 6.01$), compared to not having this knowledge ($M_{Control} = 1.06$, $SD = 7.96$, $t(477) = 2.13$, $p < 0.05$).

![Figure 1: Experiment 1 - Performance ($t_1 + t_2$)](image-url)
Next, we look at how knowledge of the 2nd best solution affects the participants’ search strategies. As can be seen in Table 1, subjects appear to use this knowledge in a variety of ways. First, and in line with what the literature predicts, we notice that the largest proportion of participants (i.e., 35.8%) interpreted knowledge about the 2nd best solution as positive knowledge, i.e., as knowledge of a solution that is worthy of exploitation in both periods, invariably leading to a payoff of 2.4.

Interestingly, our data also reveals that the second largest proportion of subjects (i.e., 24.1%) used this knowledge to exploit the 2nd best solution in t1 and then explore an unknown solution in t2. By contrast, the significantly smaller proportion of subjects who employed the opposite strategy (14.2%, z = 14.3, p < 0.001), i.e., those who searched for a solution with a higher payoff in t1 and used knowledge of the 2nd best solution as a fall back in t2 reached, in accordance to our expectations, a significantly higher performance (MExploit in T1 = 1.6, SD = 5.9, MFall back in T2 = 5.1, SD = 9.5, t(97.8) = 2.8, p < 0.01).

In addition, we also find that the third largest proportion of participants (i.e., 21.3%), which we did not find to be significantly different from the proportion who exploit knowledge of the 2nd best solutions in t1 (z = 0.85, p = 0.35), took this knowledge as negative knowledge and explored unknown solutions in both periods, reaching an even worse performance than the former group (MExploit in T1 = 1.6, SD = 5.9, MNegative Knowledge = -0.4, SD = 6.7, t(202.5) = -2.3, p < 0.05).

Finally, we notice that around 4% of the subjects acted in an irrational manner and employed what could be called, in the context of game theory (e.g., Harsanyi & Selten, 1988) a dominated strategy, i.e., a strategy that earns the participant a lower payoff than any other strategy.
Table 1: Strategies Employed in Experiment 1

<table>
<thead>
<tr>
<th>Proportion</th>
<th>Exploit in $T_1 + T_2$</th>
<th>Explore in $T_1 + T_2$</th>
<th>Exploit 2nd Best in $T_1$</th>
<th>2nd Best as fallback in $T_2$</th>
<th>Irrational Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>35.8% (N = 171)</td>
<td>21.3% (N = 102)</td>
<td>24.1% (N = 115)</td>
<td>14.2% (N = 68)</td>
<td>4.6% (N = 22)</td>
</tr>
<tr>
<td>Average Payoff (SD)</td>
<td>2.4 (0)</td>
<td>-0.4 (6.7)</td>
<td>1.6 (5.9)</td>
<td>5.1 (10)</td>
<td>3.5 (8)</td>
</tr>
</tbody>
</table>

Note. N = 478

Given that, to some participants, knowledge of the above-target solution actually hindered their search efforts, we proceed to analyze our subjects’ knowledge preferences. When we asked, after the completion of both experimental tasks, whether participants would rather be given knowledge about the 2nd best, or 2nd worst solution, unsurprisingly, 71.9% of our sample reported they would rather be given knowledge about the 2nd best solution. At the same time, when we asked them what percentage of their incentives they would be willing to pay to have knowledge of the payoff of the 2nd best solution, we found that subjects were not willing to pay more to have this knowledge ($M_{\text{Payoff of 2nd Best}} = 19.6\%, SD = 25\%$) than they would to have the knowledge that the n$^{th}$ best solution is, in fact, the 2nd best solution ($M_{\text{nth Best is 2nd Best}} = 21.1\%, SD = 24.8\%, t(422) = -1.36, p = 0.17$), or even knowledge of the performance target ($M_{\text{Performance Target}} = 21\%, SD = 24.1\%, t(422) = -1.29, p = 0.2$). Finally, we asked our subjects the extent to which their search strategies would have been different if instead of five, they were choosing between 5000 different solutions, and whether they regretted their original choices. Our results indicate that the largest proportion of participants (i.e., 28.7%) would not have changed their original search strategies and that 74.3% did not regret their original choices.

Discussion. In summary, Experiment 1 shows that possessing knowledge about the payoff of 2nd best solutions and that this solution is not the 1st best solution will lead to a
better performance than not having this knowledge. Despite the fact that a substantial proportion of our sample reached a poorer performance than they would have if they had not taken this knowledge as negative, or used it to guarantee an above-target payoff early on, the majority of subjects still saw knowledge about the 2nd best solution as positive and decided to either exploit it in both periods, or to guarantee an above-average payoff early only, allowing them to achieve a better performance than if they did not possess this knowledge.

**Experiment 2 – Search with Partial Knowledge about the 2nd best solution**

While Experiment 1 suggests that individuals may benefit from knowledge of n\textsuperscript{th} best solutions when they also know that these solutions are 2nd best solutions, in reality, this type of knowledge is rarely available in organizational contexts. More often than not, agents do not know what the 2nd best solution is, the same way that they do not know what the optimal solution is. Instead, most strategic decisions are made only on the basis of some knowledge about the payoff of different n\textsuperscript{th} best solutions and existing performance targets. With Experiment 2, our goal is to rule out the hypothesis that subjects in the treatment-group of Experiment 1 only performed better than participants in the control-group, because they knew that the current solution was not the 1st best solution.

**Control-group.** We gave the same task to the control-group of Experiment 2 as we did to the control-group of Experiment 1, i.e., we asked subjects to make two consecutive choices between five different solutions, while endowed only with knowledge about a performance target (e.g., “The average value of solutions is 0”). As was mentioned before, the only optimal strategy in this condition is a function of exploration in t\textsubscript{1}: if the payoff of the initial solution is below the performance target, than the best strategy is to explore again in t\textsubscript{2}. Conversely, if the value of the solution explored in t\textsubscript{1} is above the performance target, then the best search strategy is to exploit that same solution in t\textsubscript{2}. 

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Treatment-group. Similarly to the treatment-group in Experiment 1, participants in the treatment group of Experiment 2 were also endowed with knowledge of the performance target (e.g., “The average value of solutions is 0”). However, in contrast to Experiment 1, subjects were not given full information about the n-th best solution, i.e., they did not know that this particular solution was, in fact, the 2nd best solution, but only that its payoff was above the performance target (e.g., “Solution 3 has a payoff of 1.2”).

Sample. We obtained a final sample of 323 US Mechanical Turk Workers, between the ages of 19 and 75 (M = 37.3). We gather that 58.5% the sample in Experiment 2 is female and that the majority had participated in the study to earn some additional money (71.2%). What is more, the respondents reported an average of 2.9 years of higher education studies.

Results. We start by comparing the proportion of participants who actually find the 1st best solution in Experiment 1 vs. those who find it in Experiment 2. We should observe a lower probability of finding the optimal (or 1st best) solution if the participants in the treatment groups were more inclined to exploit their positive knowledge endowments. Conversely, if we the participants in the treatment groups were more inclined to use their knowledge endowments to look for the optimal solution, we should observe that these participants would be more likely to find this solution, compared to the participants in the control-group, given that participants in the control-groups did not have any positive knowledge to exploit in t1. Our results indicate that the participants in the treatment-group were actually less likely to find the optimal solution, suggesting that they exploited their positive knowledge endowments. Furthermore, we did not register any differences in the proportion of subjects who found the optimal solution in the two different experiments (Figure 2).
Next, we look at the overall performance across the two periods. As can be seen in Figure 3, we find that, in contrast to Experiment 1, possessing knowledge that the payoff of the 2nd best solution is above the performance target does not lead to a better performance than not having this knowledge ($M_{Treatment} = 1.28, SD = 6.3, M_{Control} = 1.36, SD = 7.9, t(322) = -0.15, p = 0.88$). Furthermore, we find that, while performance between the control-groups of both experiments does not differ significantly ($M_{Control Experiment 1} = 1.36, SD = 7.9, M_{Control Experiment 2} = 1.06, SD = 8, t(694.9) = 0.52, p = 0.6$), knowing the payoff of the 2nd best solution, and that that solution is not the 1st best solution, leads to a marginally higher performance than knowing only about the payoff of the 2nd best solution ($M_{Treatment Experiment 1} = 1.23, SD = 6.3, M_{Treatment Experiment 2} = 2.03, SD = 6, t(668.8) = -1.67, p < 0.1$).

We continue by investigating how knowledge about the payoff of the 2nd best solution (but not that that solution is either the 1st or only an n-th best solution) affects the participant’s

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We expect this difference to become significant at the $p < 0.05$ level as the ongoing collection of observation for Experiment 2 reduces the 95% confidence interval.
search strategies. As can be seen in Table 2, the participants in Experiment 2 behave in different ways than the participants in Experiment 1. Whereas the proportion of participants who see this knowledge as positive knowledge remains virtually the same (i.e., 35% in Experiment 2 vs. 35.7% in Experiment 1), the proportion of participants, in Experiment 2, who use this knowledge to guarantee an above target solution in $t_1$ and explore an unknown solution in $t_2$ is significantly lower than the proportion of participants in Experiment 1 (i.e., $M_{\text{Experiment 2}} = 17.6\%$ vs. $M_{\text{Experiment 1}} = 24.1\%$, $z = 4.33$, $p < 0.05$).

**Figure 3: Experiment 2 - Performance ($t_1 + t_2$)**

![Figure 3: Experiment 2 - Performance ($t_1 + t_2$)](image)

However, while the proportion of participants who look for a solution with a higher payoff in $t_1$ and use their knowledge as a fall back option in $t_2$ remains the same (i.e., 13.3% vs 14.2%), a significantly higher proportion of participants in Experiment 2 (i.e., 30%) took
this knowledge as negative, instead (21.3%, $z = 7.34; p < 0.01$); a shift in behavior that is responsible for the lower performance in Experiment 2.

As in Experiment 1, we also look at the subjects’ knowledge preferences. Similar to our previous results, when asked, after the completion of both tasks, whether they would rather be given knowledge about the 2\textsuperscript{nd} best, or 2\textsuperscript{nd} worst solution, participants in Experiment 2 reported that they would still prefer to possess knowledge about the 2\textsuperscript{nd} best solution (i.e., 65%); a proportion which is not significantly different from the one observed in Experiment 1. This is an interesting result because while the ideal strategy to employ when endowed with positive knowledge is ambiguous and can often lead to suboptimal results (as seen in Figure 3), knowledge about a below-target solution should always lead to a simple strategy that can improve search, i.e., avoiding that solution and exploring unknown solutions. However, despite their lower performance, participants in Experiment 2 still maintained a preference for knowledge about the 2\textsuperscript{nd} best solution.

Furthermore, in contrast to Experiment 1, when asked what percentage of their incentives they would be willing to pay for the different kinds of knowledge that they were endowed with, subjects in Experiment 2 were willing to pay significantly more to have knowledge about the performance target (i.e., the average value of solutions), than they would to have knowledge about the payoff of the n\textsuperscript{th} best solution is ($M_{\text{Performance Target}} = 21.2\%$, SD = 24.4\%, $M_{\text{Payoff of 2nd Best}} = 18\%$, SD = 22.5\%, $t(277) = 2.38, p < 0.05$). Likewise, they were also willing to pay more for knowledge that the n\textsuperscript{th} best solution was the 2\textsuperscript{nd} best solution, than they were to know the actual payoff of this solution ($M_{\text{nth Best is 2nd Best}} = 21.8\%$, SD = 23.5\%, $M_{\text{Payoff of 2nd Best}} = 18\%$, SD = 22.5\%, $t(277) = 2.47, p < 0.05$).
Table 2: Strategies Employed in Experiment 2

<table>
<thead>
<tr>
<th></th>
<th>Exploit in $T_1 + T_2$</th>
<th>Explore in $T_1 + T_2$</th>
<th>Exploit 2\textsuperscript{nd} Best in $T_1$</th>
<th>2\textsuperscript{nd} Best as fallback in $T_2$</th>
<th>Irrational Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion</td>
<td>35% ($N = 113$)</td>
<td>30% ($N = 97$)</td>
<td>17.6% ($N = 57$)</td>
<td>13.3% ($N = 43$)</td>
<td>4% ($N = 13$)</td>
</tr>
<tr>
<td>Average Payoff (SD)</td>
<td>2.4 (0)</td>
<td>-1.5 (6.5)</td>
<td>0.3 (5.7)</td>
<td>5.9 (10.2)</td>
<td>1.2 (7.5)</td>
</tr>
</tbody>
</table>

Note. $N = 323$

Finally, we asked our subjects the extent to which their search strategies would have been different if, instead of five, they had to choose between 5000 different solutions, and whether they regretted their choices. Once again, we find that the largest proportion of participants (i.e., 26.8\%) would not have changed their original strategies and that 66.3\% did not regret their original choices.

**Discussion.** In sum, Experiment 2 indicates that when individuals possess only partial knowledge about the 2\textsuperscript{nd} best solution (i.e., that this solution is above a performance target but not that it is, in fact, the 1\textsuperscript{st}, 2\textsuperscript{nd}, or 3\textsuperscript{rd} best solution) they do not make better decisions than if they did not possess any knowledge about the 2\textsuperscript{nd} best solution. We find that this is so because in the absence of full knowledge about a particular solution, a larger proportion of individuals decide to explore unknown solutions in both periods.

Furthermore, our results support the intuition that unknowledgeable agents (e.g., industry newcomers) may actually be more likely to find the optimal, or 1\textsuperscript{st} best solutions than knowledgeable ones (e.g., agents with pre-entry experience). Our results suggests that this may be the case because actors tend to stick to their prior knowledge, even if their chances of finding a better solution are higher than for unknowledgeable newcomers.
GENERAL DISCUSSION

Even though most organizations possess, at best, knowledge about $2^{nd}$ best solutions, organizational knowledge is often portrayed as a critical resource (e.g., Grant, 1996; Kogut & Zander, 1992; Szulanski, 1996). This idea is not only broadly reflected in the evolutionary and strategic management literatures (e.g., Cockburn & Henderson, 1998; Cohen & Levinthal, 1990; Kogut & Zander, 1992; Grant, 1996a; Grant, 1996b; Nelson & Winter, 1982; Szulanski, 1996), as it is also reflected in behavioral and decision-making research, where knowledge is known to play a critical role in allowing boundedly rational actors to make informed, and better decisions (e.g., Cyert & March, 1964; March, 1991; Simon, 1947, Gavetti & Levinthal, 2005, Posen & Levinthal, 2011). However, thus far, our understanding of the micro-mechanisms of knowledge utilization remains very limited.

The current work examines how organizational search and, consequently, performance is affected by positive knowledge about $n^{th}$ best solutions. We find that knowing that the payoff of an $n^{th}$ best solution clears a performance target is not always a sufficient condition for subjects to make better choices and to, consequently, reach a better performance. Instead, we observe that subjects may only benefit from their knowledge when they also know that the current solution is, in fact, not the $1^{st}$ best solution.

What is more, we find that being endowed with either type knowledge about $n^{th}$ best solutions does not seem to induce any fundamental differences in the proportion of subjects who see this knowledge as positive and who, therefore, decide to adopt the $n^{th}$ best solution. Taken together, these two experiments indicate that subjects are more likely to secure an above-target payoff early on when they know that they are dealing with $2^{nd}$ best solutions. Conversely, when subjects know only that the payoff of the current solution is above the performance target, they are more likely to take this knowledge as negative and explore other, unknown solutions. In both cases however, subjects do not predominantly employ a strategy
that looks for a better solution early on and uses knowledge about the n\textsuperscript{th} best solution as a fall back for this initial exploration; a strategy which always has a higher expected value than guaranteeing an above-target payoff early on, and later exploring an unknown alternative. Moreover, the results of the two experiments land support to the intuition that, in many industries, newcomers without pre-entry knowledge often end up finding better solutions than those who possess some form of pre-entry knowledge (e.g., Carnahan et al., working paper): if an agent initiates search with positive knowledge about an n\textsuperscript{th} best solution, the chances of the agent adopting that solution are higher than the chances of the agent looking for the optimal solution, even if the agent is theoretical more likely to do so than he did not possess that knowledge.

Because of the structural constraints to decision-making that organizations impose on their agents (Barnard, 1938) and the fact these agents do not tend to make sense of their environment based on a logic of computation, but rather based on a logic of consequences (March, 1994) and interpretation (Weick, 1969), it is important to understand how micro-level behavior affects organizational-level phenomena (e.g., Gavetti, 2005, 2012; Gibson et al, 2004; Lubatkin et al., 2006; O’Reilly and Tushman, 2011). Recent research has paid attention to this need. For example, in a recent fMRI study (Laureiro-Martinez et al., 2014), reveal that while exploration of new knowledge is associated to the activation of brain regions responsible for attentional control, exploitation of existing knowledge is in turn associated to reward-seeking brain regions, leading to a stronger activation, in anticipation of safe, predictable rewards. Furthermore, in a distinct experimental study of search in rugged landscapes, Billinger, Stieglitz and Schumacher (2014) show strong evidence for a behavioral model of adaptive search, by demonstrating that success narrows down search to the neighborhood of the status quo, while failure promotes gradually more exploratory search. We contribute to this conceptual and empirical puzzle by providing a better understanding of
how organizational search and, consequently, performance are affected by agent’s knowledge of n\textsuperscript{th} best solutions. Taken together, these findings help us better understand why agents have either been known to over-exploit suboptimal solutions (e.g., Levinthal & March, 1993), or to be too risk-averse to engage in exploratory behavior (e.g., Denrell & March, 2001; March, 1996; Nohria & Gulati, 1996).

These findings have important implications for both theory and practice. Depictions of organizations as adaptive systems often point to the positive value of organizational knowledge (e.g., Gavetti & Levinthal, 2000). However, the idea that organizational knowledge always carries a positive value is a result that we have failed to find. Instead, our results indicate that when dealing with n\textsuperscript{th} best solutions, organizations might not be necessarily better off if agents decide to act upon this knowledge, even if the knowledge in question is entirely correct and unbiased. What is more, other experimental studies have demonstrated that ignoring knowledge is often difficult (e.g., Camerer, Loewenstein, & Weber, 1989; Heath & Heath, 2006); a challenge which is typically discussed under the label of the “curse of knowledge”, i.e., the impossibility to think, or act from the perspective of an uninformed party.

**Limitations and Venues for Future Research**

One important blind spot of this work is the fact that these results haven’t yet been replicated in other contexts, such as in actual organizational environments, or in more traditional laboratory settings. Indeed, we still do not know whether the search behavior we observe might be affected by the introduction of additional factors, such as a higher number of available solutions. However, we expect that decisions made in real organizational contexts should not deviate much from the ones we observe in this study, to the extent that
the decision-making scenario imposed on these subjects (i.e., the multi-armed bandit model) has been used extensively in the past to represent search, in organizational contexts.

Moreover, we should note that the choice for a total of five available solutions in Experiment 1 was made for practical reasons, allowing us to have a performance target, a first-best solution and an \( n^{th} \) best solution above this performance target, but below the first-best solution. Nevertheless, we ended up testing a scenario in which the \( n^{th} \) best solution is always represented as being the second-best solution, even if our subjects were not aware of this. For this reason, we suggest that future studies focus on decisions made on the basis of other \( n^{th} \) best solutions.
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