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Knowledge Distance, Cognitive-Search Processes, and Creativity: The Making of Winning Solutions in Science Contests

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Abstract

Prior research has provided conflicting arguments and evidence about whether people who are outsiders or insiders relative to a knowledge domain are more likely to demonstrate scientific creativity in that particular domain. We propose that the nature of the relationship between creativity and the distance of an individual's expertise from a knowledge domain depends on his or her cognitive processes of problem solving (i.e., cognitive-search effort and cognitive-search variation). In an analysis of 230 solutions generated in a science contest platform, we found that distance was positively associated with creativity when problem solvers engaged in a focused search (i.e., low cognitive-search variation) and exerted a high level of cognitive effort. People whose expertise was close to a knowledge domain, however, were more likely to demonstrate creativity in that domain when they drew on a wide variety of different knowledge elements for recombination (i.e., high cognitive-search variation) and exerted substantial cognitive effort.

Keywords

creativity, cognition, domain knowledge, search variation, search effort, innovation, problem solving

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Who is more likely to come up with the next scientific breakthrough in the field of chemistry, a cultural anthropologist or a chemical engineer? Scholars have provided a number of strong arguments about why a chemical engineer (i.e., an insider) rather than an anthropologist (i.e., an outsider) might be more likely to demonstrate scientific creativity. After all, insiders know the territory, which is often considered to be a prerequisite for being able to make a novel contribution to a knowledge domain (e.g., Amabile, 1983; Weisberg, 1999). From a cognitive perspective, obtaining "mental representations that support reasoning" is considered a necessary first step for scientists in enabling them to generate new ideas (Ericsson, 1999, p. 332).

Historically, however, outsiders have been responsible for some major breakthroughs in various scientific domains, such as medicine (Ben-David, 1960) and biology (Mullins, 1972). Outsiders may have an advantage over insiders when it comes to solving scientific problems that require novelty because they have access to perspectives from their own domain that might be fresh and novel for the other domain (e.g., Jeppesen & Lakhani, 2010; Kuhn, 1962). In addition, the acquisition of domain knowledge has been associated with increased inflexibility (Dane, 2010; Lewandowsky & Kirsner, 2000; Sternberg & Lubart, 1995). One notable example with rich empirical evidence is the *Einstellung* effect (e.g., Bilalić, McLeod, & Gobet, 2008a; Lovett & Anderson, 1996; Luchins, 1942), which occurs "when the first idea that comes to mind, triggered by previous experience with similar situations, prevents alternatives being considered" (Bilalić, McLeod, & Gobet, 2008b, p. 553). It is often argued that such limitations occur because people's domain knowledge affects their initial mental representation of a problem and thus subsequently shapes the solutions that they come up with. With particularly intractable problems, that initial representation can be hard to shake off, even though the

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proposed solutions may have proved inadequate (Bilalić et al., 2008b; Kaplan & Simon, 1990; Smith, 1995). Because they are constantly exposed to domain knowledge, insiders are more prone than outsiders to problems of inflexibility.

Some evidence suggests that both insiders and outsiders can be a source of creative ideas; however, the precise role played by the distance between an individual's expertise and a particular knowledge domain, or *knowledge distance*, remains unclear. Perhaps the right question is not *whether* people whose expertise is distant from a knowledge domain are more likely to demonstrate creativity than those whose expertise is closer to that domain, but rather *when* they might do so. Specifically, taking into account how individuals solve problems might help to shed light on conflicting arguments about the relationship between creativity and knowledge distance; creativity is dependent not only on the initial mental representation of the problem (which is affected by the distance between one's expertise and the knowledge domain), but also on the way in which different solutions to the problem are explored (e.g., Amabile, 1983; Campbell, 1960; Schilling, 2005; Simonton, 2003). Prior research has suggested that the primary sources of creativity are cognitive-search processes (i.e., ways to explore solutions) that lead people to see novel associations between existing ideas, concepts, and knowledge elements (Hennessey & Amabile, 2010; Mednick, 1962; Mobley, Doares, & Mumford, 1992; Mumford & Gustafson, 1988). Albert Einstein, for example, emphasized the importance of novel associations for his own creative processes: "The psychical entities which seem to serve as elements in thought are certain signs and more or less clear images which can be combined. . . . This combinatory play seems to be the essential feature in productive thought" (Mednick, 1962, p. 220).

Two main cognitive processes are identified as critical for effective recombination of different knowledge elements. The first process is cognitive-search variation, or simply *search variation*, which refers to variation in terms of the knowledge elements used for recombination. This process is likely to enhance the chances of making a novel association because drawing on more elements implies a larger number of potential connections between them. Schilling and Green (2011), for example, found that when scientists draw on more knowledge domains for their articles (i.e., cite articles from a variety of disciplines), they are more likely to make atypical associations between disciplines and produce high-impact articles. The second process, cognitive-search effort, or simply *search effort*, is the amount of attention devoted to creating a novel solution and is related to the intensity aspect of attention (Kahneman, 1973). Search effort is important because it increases one's cognitive-processing capacity to notice connections between different elements and to make sense of these connections in such a way that they can be recombined to generate a novel solution to a given problem (De Dreu, Baas, & Nijstad, 2008; Li, Maggitti, Smith, Tesluk, & Katila, 2013).

Our hypothesis was that the relationship between the distance from one's expertise to a particular knowledge domain and one's creativity in that domain depends on the cognitive-search processes (i.e., search effort and search variation) in which one engages. In other words, we expected that cognitive processes that led to the spotting of novel associations (and, in turn, to greater creativity) would differ for people according to their knowledge distance. People whose expertise lay within (or close to) a particular domain were expected to see these novel associations by defocusing (i.e., seeking out a wider variety of possible knowledge sources); this would enable them to (a) avoid the tendency to gravitate toward the usual solutions and (b) increase the number of novel knowledge elements to recombine.

Going outside the domain is likely to help people overcome a fixation (e.g., Einstellung) that can arise because they are drawing instinctively on their existing domain knowledge. Therefore, going outside the domain may activate a more flexible mind-set, one characterized by avoidance of conventional routes of thinking. This sort of mind-set, which can be referred to as a *think-different mind-set*, might be helpful in going beyond typical associations between knowledge elements (Sassenberg & Moskowitz, 2005). A broader search in different domains is also likely to allow these individuals to access additional knowledge elements that they can use as a basis for forming novel associations. At the same time, using this much wider knowledge base effectively requires problem solvers to make substantial cognitive effort. This is because realizing the full potential of these diverse knowledge elements requires one to allocate significant cognitive capacity to making sense of these unfamiliar elements and exploring new connections between them (Li et al., 2013).

As knowledge distance increases, however, greater focus (i.e., limited search variation) is expected to be the mechanism through which one sees novel associations. With that growing distance, the ability to make connections between novel elements in one's own domain and the unfamiliar domain becomes vitally important in terms of finding a creative solution to the problem. Familiarizing oneself with a new domain is critical to being able to transfer novel perspectives to that domain, and a more focused search will therefore result in greater creativity than a search that covers a wide variety of domains. A focused search of this kind will require a considerable search effort because making a connection between two distant fields is cognitively demanding

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(Fleming, 2001). It is worth noting that we expect that exposure to a problem that is distant from one's field of expertise will activate a think-different mind-set for outsiders (similar to the expected impact of high search variation for insiders), and this is likely to facilitate the forming of novel associations between different knowledge elements.

We assessed the relationship among knowledge distance, cognitive processes of problem solving, and creativity in the context of science contests. Our data from 230 people who generated solutions to real science problems supported our prediction that creativity is significantly associated with the interaction between an individual's knowledge distance and his or her cognitive-search effort and cognitive-search variation.

Method

Empirical setting

This study was conducted in collaboration with InnoCentive, an online, global, prize-based science-contest platform. We selected this particular context for three reasons. First, this platform offered a unique opportunity to study the role of knowledge distance in creativity, given that people from all over the world from different backgrounds participated in these contests. Second, this platform involved real-world science problems, which typically arose in research and development departments within organizations and were thus of high external validity. Third, these contests offered great potential for finding solutions to challenging scientific problems in various scientific disciplines, and it was therefore important to have an understanding of how they worked.

InnoCentive acts as an intermediary between its clients and its community. When a client shares a specific problem with InnoCentive, the problem is posted on the InnoCentive online platform in the form of a contest. People interested in solving the problem read the description of it and submit their solutions in the form of a written report. The client assesses the submissions, selects the winning solution, and gives a monetary prize to the winner. Note that InnoCentive also posts nonscientific problems, such as those related to business models or marketing. To remain focused on scientific problem solving, we investigated two specific types of contests that focus exclusively on scientific problems: reduction-to-practice contests (i.e., those that require a detailed description of the solution and physical evidence proving that the solution will work) and theoretical contests (i.e., those that require a detailed description of the solution and supporting precedents for the solution). An example of a reduction-to-practice challenge is development of "an enzyme stabilizer at high pH"; an example of a theoretical challenge is formulation of "a simple, stable, and safe injectable suspension placebo that has no pharmacological and biological activity" (Jeppesen & Lakhani, 2010, p. 1021).

Sample and data collection

We drew on different sources of data to measure independent and dependent variables. Independent variables were measured using a Web survey, and the dependent variable was extracted from company archives. Our sample consisted of all participants in reduction-to-practice and theoretical contests in the 2.5 years before the data collection (between December 2009 and May 2012). Using contact information from InnoCentive, we sent an e-mail to 3,005 solvers. This customized e-mail contained a URL link to the survey and asked for information relating to one specific contest—the last one for which the respondent had submitted a solution. In an attempt to increase the response rate, we sent a reminder 1 week after the initial e-mail, at a different time of day on a different day of the week, and we changed the text of the initial e-mail. In total, 744 responses were received, corresponding to a 24.8% response rate. Of these, 646 (21.5%) were usable for further analysis (i.e., respondents had answered at least one question relating to the independent variables of this study). Our survey included all contests, including those that were still open, under evaluation, or withdrawn. We therefore took a subsample of contests that had a selected winner at the time of data collection. The findings reported in the article are based on the data from this subsample, which consisted of 230 respondents (207 male, 12 female, 11 with unreported gender). The average age of our sample was 44.29 years (SD = 14.44), and 82.6% had at least an undergraduate degree (for discussion and analyses relating to potential response bias, see the Supplemental Material available online).

Measures

To assess knowledge distance, we used a self-report measure developed by Jeppesen and Lakhani (2010). Respondents rated the extent to which the problem they had solved was within their field of expertise on a scale from 1 to 7 (1 = *inside my field of expertise*, 4 = *at the boundary of my field of expertise*, 7 = *outside my field of expertise*). We validated our measure of knowledge distance against experience of solving similar problems. When an individual's expertise is distant from the knowledge domain of a problem, he or she will not have been exposed to current thinking and practices in that domain (Kuhn, 1962; Weisberg, 1999) and is unlikely to have encountered similar problems. Our data confirmed this

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expectation: The correlation between knowledge distance and experience in solving similar problems was negative and significant ($r = -0.40$, $p < .001$, $N = 227$). Experience was measured by asking respondents to report their experience in solving similar problems on a scale from 1 to 7 (1 = *not experienced at all*, 4 = *moderately experienced*, 7 = *very experienced*).

Cognitive-search variation was measured with two items developed on the basis of prior literature (De Dreu et al., 2008; Schilling & Green, 2011; Simonton, 2003). Respondents were asked to indicate the extent to which they had drawn on a variety of related and different domains while developing the solution, using a scale from 1 to 7 (1 = *single domain*, 4 = *moderate variety of domains*, 7 = *wide variety of domains*; $\alpha = .89$). To avoid ambiguity, we provided the respondents with an explanatory text: "Solvers might solve the challenges by intensively using their knowledge of a single knowledge domain or by incorporating their knowledge of various domains." We validated the search-variation measure against social network ties (i.e., the number of ties contacted in relation to problem solving). Prior research identified social network ties as a main source for access and exposure to diverse information that can be used for conceptual associations (Granovetter, 1973; Perry-Smith, 2006); the number of ties should therefore be positively correlated with the variation measure. The correlation between search variation and number of ties was positive and significant ($r = 0.17$, $p = .010$, $N = 217$), confirming our expectation. The number of ties was assessed by counting how many people an individual contacted, consulted, or interacted with when devising the solution.

Cognitive-search effort was assessed by asking respondents to report how much time they had spent devising their solution—a commonly used indicator of the amount of cognitive resources expended in a task (e.g., Garbarino & Edell, 1997). Specifically, solvers were asked to indicate the total number of hours they had spent generating their final solution, and this included thinking about the solution, reading and researching it, and discussing it with other people. This variable was log-transformed because of high skewness. Single-item self-report measures of cognitive effort have been widely used in prior research, and their construct validity is extensively documented (e.g., Yeo & Neal, 2004, 2008).

With respect to the dependent variable, we calculated an individual's likelihood of proposing a winning solution to the contest (i.e., odds of winning). The data for this variable were collected from the archives of InnoCentive, and the variable was coded as 0 if a solution was not a winner and 1 if it was a winner. The main rationale behind using this variable was that a winning solution was selected on the basis of its creativity—that is, it was the most creative solution generated for a certain problem. There is no universally accepted definition of creativity, but scholars often agree that creativity involves an element of novelty and usefulness from the perspective of the domain or of the organizations concerned (Hennessey & Amabile, 2010).

To investigate the extent to which the solutions were selected according to their creativity, we conducted seven semistructured in-depth interviews with employees in InnoCentive who had extensive knowledge of how companies select winning solutions. Specifically, we interviewed all employees who were responsible for mediating the communication between companies and individual problem solvers (i.e., innovation program managers and assistants). This communication included written feedback about why each solution in our sample had or had not been a winner. These employees also worked with the companies to draw up problem descriptions, and this required them to engage in extensive discussions about what the companies expected from a winning solution. We therefore thought it was reasonable to expect these employees to be informed about the main criteria for selecting winning solutions.

The interviews confirmed our expectation that winning solutions are selected on the basis of their creativity—winning solutions demonstrate outstanding performance in terms of novelty (i.e., novel for the organization that has posted the problem and different from the solutions submitted by other participants) and are also potentially useful (i.e., valuable to the organization in terms of solving the problem). Some illustrative quotes from the interviews include: "[to win] you do not just need a solution but the most novel solution," "[companies that post the problems] evaluate . . . [solutions] on the basis of novelty and feasibility [i.e., whether it can potentially be used by the company]" or "[companies that post the problems want] a novel idea meeting all the [solution] requirements."

On a related note, because companies that post the problems provide significant monetary prizes for winning solutions and for the transfer of intellectual property rights from the winner, it might be reasonable to expect that the solution should be deemed valuable (i.e., potentially useful) and novel (i.e., different from existing solutions that the company itself may have generated). It is also worth noting that the problems in our sample were real problems that the research-and-development departments of the companies concerned have often been unable to solve. Consequently, finding answers to these problems is expected to require creativity because the solutions are not obvious, cannot be reached by following established procedures, and are not known in advance. The foregoing might suggest, therefore, that the odds of winning provide an appropriate indicator of creativity. Other scholars have also adopted a similar

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approach and used the odds of creating the most successful outcomes in creative tasks (e.g., new product ideation, academic writing, and patented inventions) as an indicator of creativity (e.g., Bayus, 2013; Schilling & Green, 2011; Singh & Fleming, 2010).

Finally, we included the total number of solutions submitted for the contest as a control variable in our model because the number of competing proposals would have a direct influence on the odds of winning (for further discussion regarding measurement protocols, see the Supplemental Material).

Results

Means, standard deviations, and correlations are reported in Table S1 in the Supplemental Material. We used a hierarchical logistic regression model to assess the interactive effects of knowledge distance, search variation, and search effort on the likelihood of generating the winning solution. To create two-way interaction variables, we multiplied standardized versions of respective variables. To create a three-way interaction term, we multiplied standardized knowledge-distance, search-variation, and search-effort variables. We entered these variables in the first step; two-way interactions between these variables in the second step; and the three-way interaction variable in the third step. The results of this analysis are presented in Table 1. As expected, the three-way interaction was significant (odds ratio = 0.48, $p = .008$). In terms of model fit, adding the three-way interaction variable in Step 3 provided an overall good fit and accounted for significantly more variance than the previous model (i.e., the model with independent predictors and two-way interactions), $\chi^2(8) = 23.09$, $p = .003$, $\Delta\chi^2(1) = 7.25$, $p = .007$. None of the other models provided as good a fit (see the footnote in Table 1).

It is also worth noting that search effort was significantly related to the likelihood of winning (odds ratio = 3.45, $p = .013$), whereas knowledge distance and search variation were not. Adding these three variables in Step 1 provided a marginally better fit than the intercept-and-covariate-only model, $\Delta\chi^2(3) = 7.18$, $p = .066$. The two-way interactions between knowledge distance and search effort (odds ratio = 1.67, $p = .080$) and between knowledge distance and search variation (odds ratio = 0.65, $p = .077$) were marginally significant, whereas the interaction between search effort and variation was not significant (odds ratio = 1.01, $p > .250$). The addition of the two-way interactions accounted for more variance than the model with independent predictors only, $\Delta\chi^2(3) = 8.60$, $p = .035$ (for a discussion of the robustness of these results, see the Supplemental Material).

To facilitate the interpretation of this interaction, we plotted how knowledge distance was related to likelihood of winning at low and high levels of search variation and search effort (i.e., at 1 *SD* below the mean and 1 *SD* above the mean, respectively). Figure 1 depicts these relationships and shows that knowledge distance was positively related to the likelihood of winning when search variation was low but search effort was

Table 1. Results of the Hierarchical Logistic Regression Analyses Predicting Winning Solutions in Science Contests

Predictor	Odds ratio	95% CI	*p*
Intercept	0.03		< .001
Number of submissions (covariate)	1.01	[1.00, 1.01]	> .250
Independent predictors (Step 1)			
Knowledge distance	0.99	[0.76, 1.29]	> .250
Search effort (log)	3.45	[1.31, 9.10]	.013
Search variation	0.94	[0.69, 1.27]	> .250
Two-way interactions (Step 2)			
Knowledge Distance × Search Variation	0.65	[0.40, 1.05]	.077
Knowledge Distance × Search Effort	1.67	[0.94, 2.95]	.080
Search Effort × Search Variation	1.01	[0.59, 1.73]	> .250
Three-way interaction (Step 3)			
Knowledge Distance × Search Effort × Search Variation	0.48	[0.28, 0.82]	.008

Note: $N = 218$. The odds-of-winning variable was coded as 0 if a solution was not a winner and as 1 if it was a winner. The intercept-and-covariate-only model did not provide a good fit, $\chi^2(1) = 0.06$, $p = .802$. Including the independent predictors in Step 1 also did not lead to a good fit, $\chi^2(4) = 7.24$, $p = .124$, $\Delta\chi^2(3) = 7.18$, $p = .066$. Adding two-way interactions in Step 2 led to a better model fit, $\chi^2(7) = 15.84$, $p = .027$, $\Delta\chi^2(3) = 8.60$, $p = .035$. Adding the three-way interaction in Step 3 provided a significantly better fit and explained more variance, $\chi^2(8) = 23.09$, $p = .003$, $\Delta\chi^2(1) = 7.25$, $p = .007$. These results and regression coefficients remained similar when the covariate was not included in the model. CI = confidence interval.

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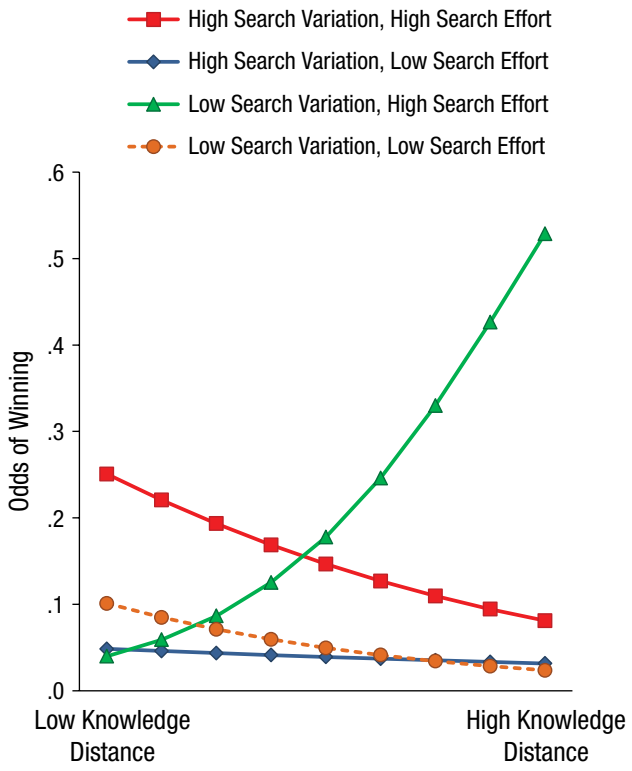

Fig. 1. The relationship between knowledge distance and odds of winning a science contest for solutions at low and high levels of search variation and search effort. *High* and *low* refer to values 1 *SD* above the mean and 1 *SD* below the mean, respectively.

high. However, knowledge distance was negatively related to the likelihood of winning when both search variation and search effort were high. The association between knowledge distance and creativity was negligible when search effort was low, regardless of whether search variation was high or low. Overall, problem solvers whose expertise was highly distant from the knowledge domain and who were engaged in a high level of search effort, but who had a low level of search variation, had the highest odds of winning the science contest.

To show how the interactive effect of search effort and search variation was associated with creativity for outsiders and insiders (i.e., for individuals who are 1 *SD* above the mean and 1 *SD* below the mean of the knowledge-distance score, respectively), we created two two-way interaction graphs (Fig. 2). Not surprisingly, for both outsiders and insiders, the odds of winning were quite low when the level of search effort was low, regardless of the level of search variation (i.e., search variation was not related to creativity when search effort was low). For high levels of search effort, variation was negatively related to creativity for outsiders, whereas this association was positive for insiders.

Discussion

In this study, we investigated how individuals' creativity in a scientific domain is related to their knowledge distance from that particular domain. Our results showed that the relationship between knowledge distance and creativity depended on the extent of cognitive-search effort and search variation. We found that individuals' knowledge distance was positively related to creativity only when they engaged in a focused search (i.e., they did not vary the search a great deal) and exerted a considerable amount of effort. However, being closer to the knowledge domain was positively associated with creativity when an individual combined a wide variety of different knowledge elements and exerted substantial search effort. It is worth noting that the creativity we refer to is closer to what some scholars call radical creativity, "big C" creativity, or eminent creativity, which concerns breakthrough ideas that are substantially different from existing ideas; this is distinct from incremental creativity, "little C" creativity, or everyday creativity, which concerns refinements, minor adaptations, or extensions of existing ideas (Hennessey & Amabile, 2010; Madjar, Greenberg, & Chen, 2011). As a whole, this study provides a cognitive account that may explain conflicting evidence with regard to the link between knowledge distance and creativity (Dane, 2010; Weisberg, 1999).

This contribution, however, must be qualified in the light of two important limitations of this study. First, the data collected in this study were correlational in nature. Although the data enabled us to observe how naturally occurring variations in knowledge distance and cognitive-search behavior were related to creativity in the solving of real-world science problems, it did not allow a precise determination of causality. We therefore encourage future researchers to use experimental manipulations to show more explicitly the causal role of search behavior in influencing creativity. The second limitation is that the independent variables of this study relied on self-report measures. Although our knowledge-distance and search-variation measures were validated against theoretically relevant constructs, and prior empirical evidence supports construct and predictive validity of self-report measures for search effort (Yeo & Neal, 2004, 2008), it would be valuable to use objective measures of these constructs in future studies. For example, social desirability might have led to biases in the measurement of our independent variables, or our respondents might not have had the ability to assess these variables accurately. This second point may not be of great concern, however, given that most of the respondents in our sample had a master's or doctoral degree in a scientific field. It might also be worth noting that the main emphasis in this work was on the interaction effect of self-report measures on an objective dependent

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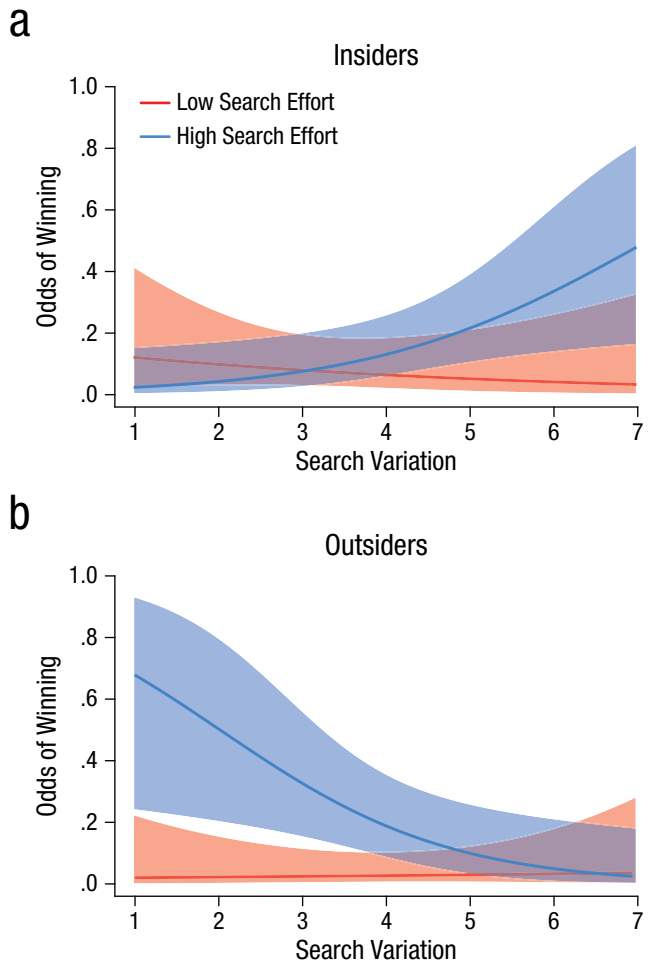

Fig. 2. Odds of winning a science contest as a function of search variation for solutions at high and low levels of search effort. Results are presented separately for (a) outsiders and (b) insiders. *High* and *low* refer to levels 1 *SD* above the mean and 1 *SD* below the mean, respectively. The shaded regions indicate 95% confidence intervals.

measure; in such cases, the chances of creating artificial links because of method biases are slim (Evans, 1985; Podsakoff, Mackenzie, Lee, & Podsakoff, 2003).

From a practical standpoint, our findings offer a way in which insiders may overcome their widely noted problems related to creativity (Sternberg & Lubart, 1995; Weisberg, 1999). That is, if insiders of a particular domain spend significant amounts of time seeking out knowledge from a wide variety of other fields, they are more likely to be creative in that domain. The findings also indicate that if solvers' attention is focused on a relatively restricted range of knowledge areas while they are also making a considerable cognitive effort, the solvers' knowledge distance can turn their lack of knowledge in a domain into an advantage. In addition, for organizers of science contests (and other organizations that aim to stimulate scientific development, such as those that provide funding for research), our results emphasize the importance of being open to those outside a scientific domain. Such organizations could take a more proactive approach to encouraging outsiders, who are more likely to solve challenging scientific problems when they engage in the "right" cognitive processes. We hope this study will help to harness more effectively the remarkable creative potential of people from a variety of knowledge backgrounds to solve significant scientific problems.

Action Editor

Leaf Van Boven served as action editor for this article.

Author Contributions

O. A. Acar developed the study concept; undertook the data collection, testing, and analysis; and drafted the manuscript. J. van den Ende supervised the data collection, testing, and analysis and provided critical revisions to the manuscript. Both authors approved the final version of the manuscript for submission.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

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References

Amabile, T. (1983). The social psychology of creativity: A componential conceptualization. *Journal of Personality and Social Psychology*, *45*, 357–376.

Bayus, B. L. (2013). Crowdsourcing new product ideas over time: An analysis of the Dell IdeaStorm community. *Management Science*, *59*, 226–244.

Ben-David, J. (1960). Scientific productivity and academic organization in nineteenth-century medicine. *American Sociological Review*, *25*, 828–843.

Bilalić, M., McLeod, P., & Gobet, F. (2008a). Inflexibility of experts—Reality or myth? Quantifying the Einstellung effect in chess masters. *Cognitive Psychology*, *56*, 73–102.

Bilalić, M., McLeod, P., & Gobet, F. (2008b). Why good thoughts block better ones: The mechanism of the pernicious Einstellung (set) effect. *Cognition*, *108*, 652–661.

Campbell, D. T. (1960). Blind variation and selective retention in creative thought as in other knowledge processes. *Psychological Review*, *67*, 380–400.

Downloaded from pss.sagepub.com by Oguz Ali Acar on May 10, 2016

Dane, E. (2010). Reconsidering the trade-off between expertise and flexibility: A cognitive entrenchment perspective. *Academy of Management Review*, *35*, 579–603.

De Dreu, C. K. W., Baas, M., & Nijstad, B. A. (2008). Hedonic tone and activation level in the mood-creativity link: Toward a dual pathway to creativity model. *Journal of Personality and Social Psychology*, *94*, 739–756.

Ericsson, K. A. (1999). Creative expertise as superior reproducible performance: Innovative and flexible aspects of expert performance. *Psychological Inquiry*, *10*, 329–333.

Evans, M. (1985). A Monte Carlo study of the effects of correlated method variance in moderated multiple regression analysis. *Organizational Behavior and Human Decision Processes*, *36*, 305–323.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, *47*, 117–132.

Garbarino, E. C., & Edell, J. A. (1997). Cognitive effort, affect, and choice. *Journal of Consumer Research*, *24*, 147–158.

Granovetter, M. (1973). The strength of weak ties. *American Journal of Sociology*, *78*, 1360–1380.

Hennessey, B., & Amabile, T. (2010). Creativity. *Annual Review of Psychology*, *61*, 569–598.

Jeppesen, L. B., & Lakhani, K. (2010). Marginality and problem-solving effectiveness in broadcast search. *Organization Science*, *21*, 1016–1033.

Kahneman, D. (1973). *Attention and effort*. Englewood Cliffs, NJ: Prentice-Hall.

Kaplan, C. A., & Simon, H. A. (1990). In search of insight. *Cognitive Psychology*, *22*, 374–419.

Kuhn, T. S. (1962). *The structure of scientific revolutions*. Chicago, IL: University of Chicago Press.

Lewandowsky, S., & Kirsner, K. (2000). Knowledge partitioning: Context-dependent use of expertise. *Memory & Cognition*, *28*, 295–305.

Li, Q., Maggitti, P., Smith, K., Tesluk, P. E., & Katila, R. (2013). Top management attention to innovation: The role of search selection and intensity in new product introductions. *Academy of Management Journal*, *56*, 893–916.

Lovett, M. C., & Anderson, J. R. (1996). History of success and current context in problem solving: Combined influences on operator selection. *Cognitive Psychology*, *31*, 168–217.

Luchins, A. S. (1942). Mechanization in problem solving: The effect of Einstellung. *Psychological Monographs*, *54*(6, Whole No. 248).

Madjar, N., Greenberg, E., & Chen, Z. (2011). Factors for radical creativity, incremental creativity, and routine, noncreative performance. *Journal of Applied Psychology*, *96*, 730–743.

Mednick, S. A. (1962). The associative basis of the creative process. *Psychological Review*, *69*, 220–232.

Mobley, M. I., Doares, L. M., & Mumford, M. D. (1992). Process analytic models of creative capacities: Evidence for the combination and reorganization process. *Creativity Research Journal*, *5*, 125–155.

Mullins, N. (1972). The development of a scientific specialty: The phage group and the origins of molecular biology. *Minerva*, *10*, 51–82.

Mumford, M. D., & Gustafson, S. B. (1988). Creativity syndrome: Integration, application, and innovation. *Psychological Bulletin*, *103*, 27–43.

Perry-Smith, J. (2006). Social yet creative: The role of social relationships in facilitating individual creativity. *Academy of Management Journal*, *49*, 85–101.

Podsakoff, P. M., Mackenzie, S. B., Lee, J., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*, 879–903.

Sassenberg, K., & Moskowitz, G. B. (2005). Don't stereotype, think different! Overcoming automatic stereotype activation by mindset priming. *Journal of Experimental Social Psychology*, *41*, 506–514.

Schilling, M. A. (2005). A "small-world" network model of cognitive insight. *Creativity Research Journal*, *17*, 131–154.

Schilling, M. A., & Green, E. (2011). Recombinant search and breakthrough idea generation: An analysis of high impact papers in the social sciences. *Research Policy*, *40*, 1321–1331.

Simonton, D. K. (2003). Scientific creativity as constrained stochastic behavior: The integration of product, person, and process perspectives. *Psychological Bulletin*, *129*, 475–494.

Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality? *Management Science*, *56*, 41–56.

Smith, S. M. (1995). Fixation, incubation, and insight in memory and creative thinking. In S. M. Smith, T. B. Ward, & R. A. Finke (Eds.), *The creative cognition approach* (pp. 135–156). Cambridge, MA: MIT Press.

Sternberg, R. J., & Lubart, T. I. (1995). *Defying the crowd: Cultivating creativity in a culture of conformity*. New York, NY: Free Press.

Weisberg, R. (1999). Creativity and knowledge: A challenge to theories. In R. J. Sternberg (Ed.), *Handbook of creativity* (pp. 226–250). Cambridge, England: Cambridge University Press.

Yeo, G. B., & Neal, A. (2004). A multilevel analysis of effort, practice, and performance: Effects of ability, conscientiousness, and goal orientation. *Journal of Applied Psychology*, *89*, 231–247.

Yeo, G. B., & Neal, A. (2008). Subjective cognitive effort: A model of states, traits, and time. *Journal of Applied Psychology*, *93*, 617–631.

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