PROJECT SUMMARY

Overview:

When generating and developing creative ideas, does it pay more to draw inspiration from information and ideas that are more or less similar to the problem one is working on? In a similar vein, is it better to draw from more or less diverse sources of inspiration? This project will examine these questions in the context of a large-scale Web-based social innovation platform that recruits thousands of motivated and knowledgeable people to develop creative solutions to such problems as youth unemployment, urban community disengagement, and accumulating e-waste. This project will examine 2,344 concepts for 12 different social innovation problems; these concepts draw on more than 6,000 unique sources, which are explicitly cited on the network, creating a ready-made web of source-concept connections that will be mined for insights on the relationship between source conceptual distance/diversity and creative success. Data mining methods will be adapted to this context in order to address the challenge of measuring conceptual distance for this many concepts and sources; human judgments of conceptual distance will be collected to validate and enrich this analysis of conceptual distance. Statistical modeling will be employed to determine how variations in source conceptual distance (both from the problem domain and between sources) predict the outcomes of concepts (i.e., whether or not they are chosen by a panel of experts for development or implementation) after accounting for key control and confounding variables (e.g., source quality, amount of feedback from others, author expertise).

Intellectual Merit :

In the creative process, people inevitably build new ideas from sources of inspiration, most often from their prior knowledge and experiences, whether old or recent, consciously or unconsciously acquired. These sources of inspiration can lead one astray (e.g., incorporating undesirable features from existing solutions, difficulty considering alternative approaches), but sometimes be key drivers of creative breakthroughs. Therefore, to understand how creativity happens, it is of crucial importance to discover scientifically-based principles for curating and using sources of inspiration in the creative process so as to maximize creative success (i.e., the creation of artifacts that are both novel and add significant value over existing or prior creations). This project works toward that end by examining the hypotheses that the odds of creative success are maximized when one builds more on sources that are conceptually far from one?s problem, and draws on a conceptually diverse set of sources. These hypotheses are important to consider because they are widespread in both the scientific literature and among creative practitioners, and yet both receive only partial or mixed empirical support. This project addresses some key challenges to rigorous and informative tests of these hypotheses ? including the difficulty of observing creative processes at realistic time scales and with enough observations to make reliable statistical inferences, and conceptual and methodological difficulties and inconsistencies in the measurement of conceptual distance ? by adapting methods from machine learning to analyze many cases of creating (on the order of thousands) over the course of weeks in a real-world innovation context. The results of this project will not only advance scientific theories of creativity, but also advance scientific methods for studying the creative process.

Broader Impacts :

In today?s global knowledge-based economy, nations, corporations, and individuals need to innovate to survive and thrive. There is a pressing need for scientific principles that can guide efforts to train and support innovation. This project will contribute actionable knowledge toward that end, specifically yielding insights that have implications for the increasingly widespread design and use of computer-supported creativity (e.g., automated knowledge discovery, Web-based innovation platforms) and for the grooming of tomorrow?s innovators, all contexts in which the question of how to curate and use sources of inspiration is both fundamental and yet lacking firm answers. To ensure impacts, knowledge gained from this project will be shared in outlets where researchers and practitioners in innovation-relevant disciplines (e.g., engineering design methodology, human-computer interaction) work hand-in-hand. The PI and Co-PI?s existing connections to engineering education and innovation consulting will also be leveraged to ensure fruitful knowledge transfer.

C. PROJECT DESCRIPTION

I. MOTIVATION AND OVERVIEW

Creativity and innovation are crucial mainstays in modern society. Continued innovation is a central driver of today's knowledge-based economy; in order to survive and thrive, firms can no longer depend on commoditization and scale — they must innovate or die (Vogel, Cagan, & Boatwright, 2005). The U.S., too, needs innovation to continue thriving in an increasingly globalized and knowledge-driven economy (National Academy of Engineering, 2005). Further, complex problems facing modern society, such as global poverty, e-waste, cancer, and climate change, are more pressing than they have ever been, and call for new innovative solutions. There is now a pressing need for innovators who can rise to these challenges. How can governments, organizations, and training programs effectively train and support such innovators? A crucial part of the puzzle is a robust scientific knowledge base that articulates key principles of how creativity happens. Cognitive science offers a key piece of this knowledge base, focusing on the creative process (including mental processes and strategies) that lead to creative breakthroughs.

One of the most robust and established insights from the cognitive science of creativity is that the creation of new ideas is strongly constrained or structured by prior knowledge and experience. People have a strong tendency to transfer features and elements from recently encountered stimuli or examples in their creative production, often despite instructions to avoid such copying (Jansson & Smith, 1991; Marsh, Bink, & Hicks, 1999; Marsh, Ward, & Landau, 1999; Perttula & Sipilä, 2007; Purcell & Gero, 1992, 1996; Smith, Ward, & Schumacher, 1993; Ward, 1994). This tendency towards transfer can harm creativity. Some experiments have shown that people will transfer elements from examples even when those examples are known to be of low quality (Chrysikou & Weisberg, 2005; Jansson & Smith, 1991). Prior knowledge can also lead to functional fixedness — the inability to see novel uses for an artifact due to prior conceptions of its dominant functionality (Adamson, 1952; German & Barrett, 2005; Maier, 1931) — and mental set effects (also called Einstellung) — where people persist in using previously successful solution approaches in problem solving without considering alternative, potentially more effective, approaches for the current task at hand (Bilalić, McLeod, & Gobet, 2008; Luchins, 1942; Öllinger, Jones, & Knoblich, 2008; Wiley, 1998).

However, this tendency to base creative production on prior knowledge is not an inherent detractor from creativity. Purcell and Gero (1996) have argued that fixation is an imprecise (and perhaps incorrect) term for this phenomenon: when the examples are innovative or of high quality, the transfer may increase the creativity of the final product. Conformity to examples does not necessarily influence other key process measures of creativity, such as quantity or elaboration of concepts generated (Marsh, Landau, & Hicks, 1996), and, depending on features of the source (e.g., novelty, conceptual distance from domain), may also increase the quality of ideas (Ward, 2008), or also novelty of ideas (Chan et al., 2011; Smith, Kohn, & Shah, 2008).

For these reasons, intentional curation of the building blocks of prior knowledge/experience—hereafter called **sources of inspiration**—is a crucial component of effective creative practice. Tradecraft literature (e.g., books, blogs) is replete with advice and support for curating sources of inspiration: Henry (2011) urges creators to carefully curate stimuli to keep their creative fuel burning, and Dyer and colleagues (2011) urge innovators to keep their "pool of available bricks" in memory fresh, to increase the probability that truly breakthrough concepts can be generated. Detailed ethnographic studies of successful innovators and creators have also corroborated the central role of curating and intentionally interacting with sources of inspiration (Eckert & Stacey, 1998; Hargadon & Sutton, 1997; Herring et al., 2009). Further, the issue of how to prevent and/or alleviate design fixation is an active area of research in design methodology research (Linsey et al., 2010; Youmans, 2011; Zahner et al., 2010).

But *how* should one curate one's sources of inspiration? Or to pose the question more precisely, **what principles should guide the curation and use of sources of inspiration in the creative process such that creators can benefit from them while avoiding their potential pitfalls?** One key facet of this question concerns the nature of the sources themselves: are there particular features or properties of inspirational sources (e.g., conceptual distance to the problem, conceptual diversity among considered sources) that provide reliable signals of greater or lesser inspirational potential?

I propose to address these fundamental questions with quantitative analyses of creative processes and outputs of individuals solving real-world creative design problems, focusing on the issue of conceptual distance. I focus on this issue given the discrepancy between the widespread claims offered in the scientific literature and among practitioners as to how conceptual distance of and between sources can matter for creative outcomes, and the strength (or lack thereof) of the evidence base for these claims. This presents an opportunity for significant knowledge gains to be made, in contrast to other relatively uncontroversial claims regarding the nature of sources (e.g., build on high-quality solutions).

More specifically, I propose to study the dynamics of inspiration source use, ideation, and creative outcomes in the context of OpenIDEO (www.openideo.com), a large-scale Web-based crowd-sourced innovation platform where thousands of individuals have been coming together to collaboratively solve a wide range of socially and environmentally important problems (e.g., managing e-waste, increasing accessibility in elections, restoring community in socially fragmented cities). Contributors to the platform follow a structured design process — starting from initial problem structuring, through concept generation and screening, to refinement and evaluation of concepts — to produce concepts that are ultimately implemented by the challenge sponsors, producing real-world impact. I propose to study how variations in conceptual distance of sources from the problem domain, and conceptual distance *among* sources, relate to creative success (i.e., the creation of designs that are both novel and add significant value over existing designs).

The results of this work will have critical implications for the specific question of what principles should guide the curation of inspiration sources, and also more generally for efforts to understand and maximize creativity and innovation, from the design and implementation of innovation support tools and methods (e.g., computer-aided design, formal design-by-analogy methods), to the new wave of creative crowdsourcing platforms (similar to OpenIDEO), to creativity education in the disciplines, to the intentional design of creative social spaces (e.g., R&D centers, innovation hubs).

II. STATE OF THE ART AND RESEARCH GOALS

II.A. Investigating The Effects Of Source Conceptual Distance From Problem Domain

II.A.1. State of the art

The first major initiative of the proposed work will investigate the hypothesis that, in curating sources, one should prefer sources that are conceptually far from one's problem domain. For instance, consider the problem of e-waste accumulation, with 20-50 million metric tons of e-waste generated worldwide every year, and the vast majority of it ending up as environmentally hazardous additions to landfills. An innovator developing fresh, creative approaches to addressing this globally pressing problem might build on smaller-scale electronics reuse/recycle efforts (**near** source), or draw inspiration from edible food packaging technology or labeling of appliances as "energy-efficient" (**far** sources); the hypothesis being investigated is that a breakthrough creative solution is more likely in the latter case.

Theoretical foundations. The major theoretical impetus for this hypothesis comes from work on analogy, a fundamental cognitive ability to flexibly perceive two things as functionally or relationally similar (French, 2002; Gentner & Forbus, 2011), even when they are dissimilar with respect to their "object features" (e.g., color, size, geographical location). Analogy has been widely implicated in creative thought, perhaps most prominently in scientific discovery (Clement, 1988; Dunbar, 1997; Holyoak & Thagard, 1996a; Nersessian, 1992; Thagard, 2008) and — the focus of this work — technological invention and innovation (Carlson & Gorman, 1990; Gorman, 1997; Linsey, Murphy, Laux, Markman, & Wood, 2009; Perkins, 1997). It is also an important component of many creative problem solving methodologies, such as Gordon's (1961) Synectics, Altshuller's widely used Theory of Inventive Problem Solving (or TRIZ; Savransky, 2000), and the burgeoning field of biomimetic design (Chakrabarti et al., 2005; Hacco & Shu, 2002; Helms, Vattam, & Goel, 2009).

Most pertinent is the idea, espoused by a number of theorists (Gentner & Markman, 1997; Holyoak & Thagard, 1996b; Poze, 1983; Ward, 1998), that "far" analogies —structural similarity with many surface (or object) dissimilarities (e.g., the atom/solar system analogy) — hold more potential for generating creative ideas than "near" analogies. This idea is consistent with many anecdotal accounts of creative insights, from Kekule's discovery of the structure of benzene by visual analogy to a snake biting its tail (Findlay, 1965), to George Mestral's invention of Velcro by analogy to burdock root seeds clinging to dog fur (Freeman & Golden, 1997), to more recent case studies (Enkel & Gassmann, 2010; Kalogerakis, Lu, & Herstatt, 2010).

Far sources may uniquely support higher levels of creativity because crucial insights to creative problems may lie outside one's working domain, whether because of inappropriate constriction of the problem domain (due to suboptimal mental representation of the problem space, cf. Einstellung and functional fixedness), or because these insights actually lie outside of one's discipline or general domain, as evidenced by the rise of collaborations and interdisciplinarity in science and technology (Jones, 2009; Paletz & Schunn, 2010; Wuchty, Jones, & Uzzi, 2007). Ideas in social network theories of innovation also emphasize the privileged position of agents positioned in "structural holes" in the information network (Burt, 2004; Hargadon, 2002; Ruef, 2002; Tortoriello & Krackhardt, 2010), being able to bridge knowledge and resources from structurally separated regions of the network.

In addition to direct transfer of insights, far sources may also act as a "bridge" to dormant but relevant prior knowledge through spreading activation in memory. Surface dissimilar but relevant knowledge and experiences in long-term memory can be reasonably accessible if they are well-learned or connected to one's area of expertise (Blanchette & Dunbar, 2000, 2001; Chen, Mo, & Honomichl, 2004; Novick, 1988), but surface dissimilar knowledge and experiences recently acquired may lie inert in memory, even if they provide crucial insights for the problem (Day & Goldstone, 2012; Gick & Holyoak, 1980, 1983; Reed, Ernst, & Banerji, 1974), in part due to the strong influence of surface similarity on memory retrieval (Forbus, Gentner, & Law, 1994; Gentner & Landers, 1985; Gentner, Rattermann, & Forbus, 1993; Keane, 1987; Ross, 1987).

Empirical foundations. At present, the empirical foundation for greater benefits of far sources on creativity is mixed. Dahl and Moreau's (2002) foundational study on the effects of conceptually far sources is most often cited in support of the benefits of preferring far sources. In their study, 119 senior engineering students attempted to solve a novel design problem, and were encouraged to use analogies while doing so. Dahl and Moreau found that the proportion of far analogies used by a given participant was a statistically significant positive predictor of the rated originality of his/her design, as well as a customer panel's average willingness to pay for it; in other words, this oft cited source is rather indirect support for the beneficial effects of far analogies. A few other studies have replicated the basic finding of the advantage of far over near sources for quality and flexibility of ideation, in addition to novelty of ideas (Chan et al., 2011; Chiu & Shu, 2012; Gonçalves, Cardoso, & Badke-Schaub, 2013; Hender, Dean, Rodgers, & Jay, 2002). However, there are important caveats, e.g., reduced idea generation rates (Chan et al., 2011; Hender et al., 2002), non-replication with some design problems (Chiu & Shu, 2012), and lack of conventional statistical significance (Gonçalves et al., 2013). Additionally, some *in vivo* studies of creative discovery have failed to find strong connections between far sources and creative mental leaps (Chan, 2012; Dunbar, 1997), and other experiments have demonstrated equivalent benefits of both far and near sources for creative outcomes (Enkel & Gassmann, 2010; Huh & Kim, 2012; Malaga, 2000; Tseng, Moss, Cagan, & Kotovsky, 2008).

This mixed empirical foundation represents an important gap in the literature, and a potential opportunity for theoretical progress. It may be critical to integrate key moderators, such as expertise (Goldschmidt, 2001; Novick, 1988), timing (Kulkarni et al., 2012; Seifert, 1995; Tseng 2008), or problem characteristics (Chiu & Shu, 2012; Goldschmidt & Smolkov, 2006; Holyoak & Thagard, 1996b). Alternatively, it may be necessary to abandon the theory that far sources uniquely support creativity, in line with theorists like Perkins (1983), who argues that conceptual distance does not matter, and Weisberg (2009), who argues that within-domain expertise and knowledge is a primary driver of creativity. I argue that a crucial prior and/or complementary step to these potential theoretical moves is a solidification of the empirical evidence base, specifically by addressing some key methodological issues. These issues motivate key design features of the proposed work, and will be fleshed out further in the next sections.

II.A.2. Research goals

In addition to addressing new research questions, the proposed work addresses three overarching methodological issues in the prior research literature: 1) inconsistencies in the measurement of conceptual distance, 2) inappropriate time scales, and 3) lack of statistical power. I discuss these issues in turn, and highlight how the proposed work addresses them.

Measurement inconsistencies. Most studies use a binary within- vs. between-domain measure (Chan et al., 2011; Chiu & Shu, 2012; Dahl & Moreau, 2002; Huh & Kim, 2012; Tseng et al., 2008; Wilson, Rosen, Nelson, & Yen, 2010), while a few others used a binary near vs. random measure (Hender et al., 2002; Malaga, 2000), three levels of distance (near, far, and random; Dunbar, 1997; Gonçalves et al., 2013) or some sort of continuous measure (Enkel & Gassmann, 2010).

Recent work suggests that unpacking conceptual distance beyond simple near/far might enable reconciliation of opposing findings. Fu et al. (2013) found opposing results to Chan et al. (2011) — i.e., far sources harming instead of benefiting ideation — despite using the same design problem, participant population, and source search space. To make sense of the contradiction, the second paper employed a combination of Latent Semantic Analysis (Landauer & Dumais, 1997) and Bayesian structure learning (Kemp & Tenenbaum, 2008) to model the conceptual distance of the 2011 and 2013 sources within the same space, along with 100 other sources from the same general domain (mechanical engineering). Figure 1 illustrates the result of this analysis: the 2011 *near* sources clustered most closely around the design problem, followed by the 2011 *far* source, then the 2013 *near* sources, and with the 2013 far sources dispersed far from any of these sources. This unified distance scale led to hypothesizing a "sweet spot" (or curvilinear) effect of distance, such that "slightly far" (i.e., not in the *immediate* problem domain, but conceptually quite close), but not "too" far sources seem most beneficial. While provocative, there is a need to establish the generality of this inverted-U pattern across problems (only one design problem was used in Chan et al. 2011 and Fu et al. 2013), and across a wide range of conceptual distances (more than just 4 points on a continuum).

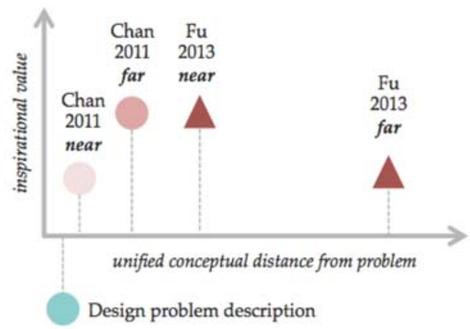

Figure 1: Illustration of unified distance scale analysis in Fu et al. 2013

The proposed work will build on this approach, using both traditional within- vs. between-domain and continuous measures of conceptual distance, and with a much larger source set (thousands as opposed to tens). While there are reasons to doubt the utility of binary approaches (e.g., lack of granularity, redundancy with continuous measures), within- vs. between-domain approaches permit a relatively constant and comparable measure across problems, which may not be possible with existing continuous approaches.

Time scale. 30 minutes to 1 hour problem solving time used in typical experiments and/or protocol studies may be too short to observe the potential long-term payoffs of cross-domain inspiration. Perkins (1997) has observed that analogies (especially far ones) carry with them the risk of combinatorial explosion of poor alternatives. That is, most sources in a conceptually distant domain are likely to be irrelevant or yield unusable inferences (e.g., due to non-alignable differences in structure or surface features), analogous to the risk associated with the exploration side of the exploitation/exploration dilemma in the study of adaptive systems (Holland, 1975; March, 1991; Schumpeter, 1934). In addition, with far sources scarce cognitive resources are required to ignore irrelevant surface details and attend to potentially insightful structural similarities. This might partially explain losses in fluency sometimes observed with the use of far sources (Chan et al., 2011; Hender et al., 2002). Further, typical study designs impose a rigid separation between ideation and implementation phases, which — while consistent with formal process models of the creative process — cannot capture the iterative, piecemeal nature of creation, with inspiration from sources and ideation being interleaved with later execution processes as new knowledge is gained from initial prototyping, sketching, etc. (Dow, Heddleston, & Klemmer, 2009; Schön, 1983, 1992). Finally, the relative costs of processing far sources are far higher in a shorter time scale than in a more realistic time scale (e.g., the duration of a project, ~weeks/months), e.g., 20 minutes is a substantial cost when the ideation phase is 1 hour long, but negligible in a time span of weeks/months.

These observations suggest that the choice of time scale when observing the effects of far sources may critically influence the accuracy of the inferences drawn about the relationship between conceptual distance and creative outcomes. At shorter time scales, creators might not have enough samples to hit the low probability-but-high-return far source needed to generate the expected high inspirational payoff, or sufficient resources available to overcome the cognitive overhead of mapping/adapting far sources to the problem; additionally, observation at this time scale might miss crucial pieces of inspiration that come after initial ideation. Studies using a more realistic time scale are critical for addressing these issues and ensuring that far sources are given a "fair chance" to show their benefits.

This issue motivates the choice of OpenIDEO as the context for this investigation: concepts in OpenIDEO are developed over the course of weeks, in contrast to the typically-studied time scale of minutes or hours, and contributors often iterate and prototype on their concepts throughout the challenge. I believe that these important features of the data will either allow for observation of the benefits of far sources, or (if no benefits are observed), to at least rule out time scale as an alternative explanation for failing to observe these benefits.

Statistical power. Among existing experimental studies, most have an N of 12 or less per treatment cell (Chiu & Shu, 2012; Hender et al., 2002; Malaga, 2000; Wilson et al., 2010); only 3 studies had an N of 18 or better per cell (Chan et al., 2011; Gonçalves et al., 2013; Tseng et al., 2008), a sample size that would begin to approach acceptable levels of statistical power to detect medium-sized effects. Among the few correlational studies, only Dahl and Moreau (2002) had an acceptable study design in this regard, with 119 participants and a reasonable range of conceptual distance. Enkel and Gassmann (2010) only sampled 25 cases, and suffers from range restriction because they only sampled cases of cross-industry transfer. Combined with the potential issue of time scale (small or potentially zero effects at short time scales), the mixed empirical evidence base may reflect the proliferation of false negatives due to insufficient power; however, the predominance of underpowered designs may also mean that some of the reported effects are severely overestimated or spurious (Button et al., 2013; Gelman & Weakliem, 2009).

The proposed work addresses this deficiency by analyzing the development and outcomes of over 2,000 concepts, submitted by approximately 1,000 authors. This sample size is sufficient to model the effects of conceptual distance on creative outcomes, over and above other control variables that need to be accounted for due to the observational nature of the dataset (e.g., author effects, quality of sources).

Research Question #1: What are the relative benefits of different levels of source conceptual distance for creative outcomes?

In summary, the first goal of the proposed work will be to address the already explored but central question of the relative benefits of different levels of source distance, now using multiple distance measures, a realistic observational time scale, and high statistical power.

II.B. Investigating The Effects Of Source Conceptual Combination Distance

II.B.1. State of the art

The second major initiative in the proposed work will investigate the related but distinct hypothesis that, in using sources of inspiration, one should attempt to connect sources and concepts that are conceptually far from each other. In the course of a concept's development, designers often build on ideas from more than one source (e.g., different approaches for a single sub-system, different sources for different sub-systems). Consider again an innovator developing creative solutions for the problem of e-waste accumulation. That innovator might build on related but slightly different approaches to educating about e-waste, such as classroom curricula, video education series on Youtube, and on-label information about reuse/recycle options (**near** combinations); alternatively, he might combine concepts from gamification, social media campaigning and marketing, and exercise and dieting lifestyle-change mobile applications (**far** combinations). The hypothesis being investigated is that a breakthrough creative solution is more likely in the latter case.

This hypothesis is related to the "far source" recommendation, but distinct in that it does not necessarily distinguish between combining sources that are far from each other *within* the problem domain (e.g., combining a bus and a plane to come up with a new transportation system) and far combinations from within to outside (e.g., combining a bicycle and a printer), or to sources outside the problem domain (e.g., combining a heart defibrillator with geese migration patterns). Figure 2 illustrates the range of possible variations in source sets by distance from domain and distance of combination. It is important to understand not just how each dimension of conceptual distance influences ideation separately, but also how they might interact.

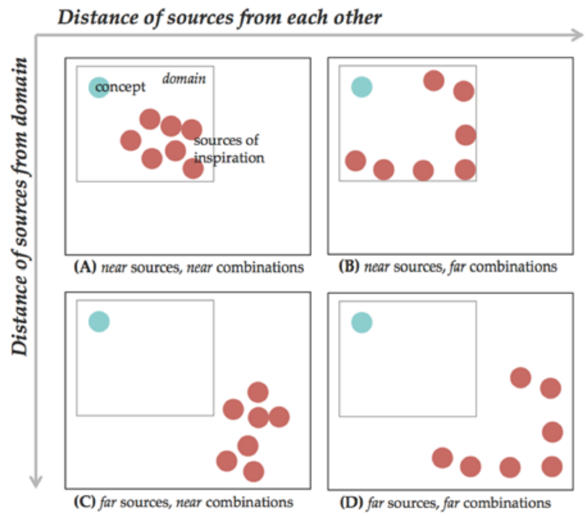

Figure 2: Illustrated variations of inspiration source sets

Theoretical foundations. The recommendation to prefer far combinations has its roots in Mednick's (1962) influential claim that "[t]he more mutually remote the elements of the new combination, the more creative the process or solution" (p. 221). Further, theorists who analyze tecnological innovation through studying patent citation networks contend that patents that reference other patents from a wide number of technology areas hold more potential for radical innovation compared to patents that reference other patents in similar technology areas (Olsson, 2005). Recent social network theories of innovation have similarly emphasized the importance of combining information from diverse sources as a basis for innovation (Vedres & Stark, 2010).

Far conceptual combinations might support creative breakthroughs via the generation of emergent features when trying to combine them. Research on conceptual combination suggests that, when concepts are very different, people switch from relatively simpler combination processes — such as attribute inheritance/transfer or property mapping (Hampton, 1987; Wisniewski & Gentner, 1991) — to more complex processes, such as structure mapping (Gentner et al., 1997), which can generate emergent features (attributes that are true of neither constituent, but true of the conjunction; Hampton, 1997). Relatedly, the degree to which emergent features arise from combinations has been found to be an inverse function of the conceptual similarity between the constituent concepts (Wilkenfeld, 1995; Wilkenfeld & Ward, 2001; Wisniewski, 1997). Thus, combining concepts that are conceptually far from each other is likely to result in original features and functions that might prove to be crucial components of a creative breakthrough.

Far combinations may also protect against fixation: considering sources far from each other in conceptual space may prevent one from getting too strongly stuck in one region of the conceptual space, perhaps due in part to the distribution of memory activation across a wider range of features and functions. Another possible inspirational mechanism of far combinations (or at least having a diverse set of sources to draw from) is the increased statistical probability of finding an interesting and potentially useful combination (Simonton, 1988), although this mechanism might only operate if the set consists mostly of useful rather than completely irrelevant sources.

Empirical foundations. Several lines of evidence support the idea that far combinations undergird creative thinking. First, there are many anecdotes of creative breakthroughs coming from far combinations, such as award-winning chef Samuelsson's fusion Swedish cuisine, Grammy-winning singer-songwriter Shakira's fusion of Latin and hip-hop musical sounds, and the highly successful Magic collectible cards game, which combined concepts from collectible items (such as baseball trading cards) and ordinary games (Johansson, 2006). Experimental and observational studies also provide converging evidence. The ability to create high-quality and original emergent features from conceptual combinations has been associated with performance on creative problem-solving tasks (Mumford, Baughman, & Sager, 2003). Generating ideas using stimuli from different categories have been shown to yield more novel ideas than using stimuli from similar (or the same) categories, both in simple brainstorming experiments with toy problems (Baughman & Mumford, 1995; Howard-Jones, Blakemore, Samuel, Summers, & Claxton, 2005; Zeng, Proctor, & Salvendy, 2011), with more realistic creative tasks like graphic design or business opportunity identification (Chase, Herman, & Dow, 2012; Gielnik, Frese, Graf, & Kampschulte, 2011), although sometimes at the expense of idea quality (Mobley, Doares, & Mumford, 1992). Baruah (2011) found no positive effect on originality, but did find a positive effect on breadth of search, with participants who were stimulated with distantly related categories surveying more idea categories than participants stimulated with closely related categories. Nijstad and colleagues (2002) demonstrated similar benefits of stimuli diversity on breadth of search. In a more ecologically valid setting, Taylor and Greve (2006) showed that comic book creators' diversity of prior genre experience positively predicted creative performance (measured in terms of collector market value of comics produced). In general, the literature provides support for a link between distant combinations and the novelty of ideas generated, but most studies (except Taylor & Greve, 2006) have not yet looked carefully at whether there is an effect on final quality of ideas.

II.B.2. Research goals

The proposed work aims to build on this existing work by addressing the issue of the relative importance of novelty. While it seems clear that far combinations have high potential for generating novel emergent features, it remains an open question whether these features are likely to be beneficial additions to the resulting concept in terms of functionality or appropriateness. The consensus in the literature is that creative products need to be both novel and appropriate (Boden, 2004; Sawyer, 2012). Particularly in technical domains, such as science and engineering (the focus of the proposed work), creativity does not arise from novelty *per se*; rather, novelty only enters into creativity insofar as it adds value, e.g., helping to solve a conceptual puzzle, adding or improving functionality. Thus, there is a need to study the effects of far conceptual combinations on idea *quality* in addition to novelty.

Research Question #2: What are the relative benefits of different levels of conceptual combination distance for creative outcomes?

The second goal of the proposed work will be to study the effects of combination distance on the probability that a given concept will be chosen by a panel of expert judges for refinement (indicating creative promise) and/or implementation (innovation). This outcome measure combines signals of novelty and quality, and will allow for more grounded inferences about the effects of far combinations on *creative* outcomes (not just novelty or fluency/breadth of search).

III. RESEARCH APPROACH

III.A. Additional Relevant Details On Dataset

External validity. The research context, as mentioned is the OpenIDEO innovation challenge platform (www.openideo.com). To contextualize the discussion of the data collection and measure derivations, it is useful to consider some additional details about the OpenIDEO dataset. The first critical detail is the high external validity of the context. OpenIDEO's focus on social and environmental problems encourages participation by a combination of experienced "creatives" from a variety of disciplines (e.g., user experience/interface design, industrial design, business entrepreneurs and executives) and motivated non-designers with domain-specific knowledge or experiences relevant to the challenge. Thus, the people being studied in this dataset are closer to creative practitioners (either domain-general creative practitioners or motivated domain experts) than the typical psychological study using convenience samples of undergraduate students. Additionally, the highly collaborative, crowdsourced nature of the platform is representative of important developments in innovation approaches, with the rise of crowdsourced creativity platforms (e.g., www.innocentive.com, www.quirky.com), innovation tournaments (Terwiesch & Ulrich, 2009), and open innovation. Scientific theories of creativity should be concerned not just with individual inventors or small teams, but also with this wave of social-organized creativity, which will only become more prominent.

Structured design process. The second detail involves the structuring of challenges into distinct phases (see Table 1). This structured process and guidance by the OpenIDEO team (who are expert designers) and challenge sponsors (who are domain experts) helps ensure that the process and outcomes are of high quality, and bolster confidence that effects observed here will generalize to other real-world creative settings. This structuring of the design process still allows for iteration in concept generation, as authors can prototype and refine concepts throughout the challenge, incorporating new sources of inspiration if they are deemed to add further value.

Table 1: OpenIDEO structured design process

Phase	Description
Challenge start	Community receives challenge brief; problem broadly framed; initial constraints/requirements described
Inspiration	Community submits, "applauds" (i.e., votes on), and gives feedback on inspirations (e.g., descriptions of solutions to analogous problems, case studies of stakeholders); problem space defined in more detail, promising solution approaches ("themes") identified by administrators/sponsors; 117 to 894 inspirations per challenge (380 on average)
Concepting	Community submits, applauds, and gives feedback on concepts (proposed solutions to problem); 92 to 612 concepts per challenge (195 on average)
Screening	Using applause as input, administrators & sponsors *shortlist* subset of concepts (16 to 25, 20 on average) for further refinement
Refinement	Community collaborates with authors to improve shortlisted concepts
Evaluation	Community provides focused evaluations of shortlisted concepts based on administrator & sponsor-defined challenge-specific evaluation rubrics
Realization	Administrators & sponsors select winning concepts (6 to 11, 10 on average) for implementation

Nature of concepts and sources of inspiration. A third detail concerns the nature of the inspirations and concepts posted in the *Inspiration* and *Concepting* phases of each challenge (see Table 1). Inspirations and concepts can include visual elements (e.g., figures/videos); however, most concepts/inspirations have the bulk of their descriptions in the text, and all of them have an "abstract" at the beginning that summarizes the contribution. Inspirations are on average about 80 words long, while concepts are on average about 150 words long. Concepts also include answers to 3-5 administrator-provided questions that probe thinking about key challenge requirements and implementation considerations, and authors often describe potential implementation scenarios (and in some cases, insights from prototyping efforts); thus, most concepts are described in more detail than one or two words/sentences/sketches, but not in as much detail as a design report. This lends extra credibility to the evaluation process, which is based on a combination of evaluating concepts' novelty, promise of impact, and implementability with current or near future resources. That is, the concepts are sufficiently detailed to evaluate, in contrast to many ideation studies that have short phrases or a few words for each concept that are generally hard to evaluate. Figure 3 shows a representative concept (drawn from the e-waste challenge).

Encouraging citations of sources of inspiration. A fourth critical detail concerns the explicit role of sources of inspiration in the OpenIDEO concepting process. Contributors are encouraged to build on others' ideas. Explicit citation of concepts and inspirations being built upon is central to the user interface for posting contributions to the platform: when posting concepts or inspirations, contributors are prompted to cite any concepts or inspirations that serve as sources of inspiration for their idea, and when browsing other concepts/inspirations, they are able to also see concepts/inspirations the given concept/inspiration "built upon" (i.e., cited as explicit sources of inspiration). In addition, while looking at individual concepts or browsing posted concepts, at any time users can launch a "collaboration map" feature that allows them to visually browse citation relationships between concepts and inspirations in the challenge. This culture of citing sources is particularly advantageous for research, given that people generally forget to monitor or cite their sources of inspiration (Brown & Murphy, 1989; Marsh, Landau, & Hicks, 1997), and my goal is to study the effects of source use. While some forgetting of sources is still likely to happen, these platform features are likely to yield higher rates of source monitoring than in other contexts (e.g., observational/experimental studies of ideation).

Multiple design problems. Finally, the existence of multiple challenges is a useful feature of the dataset. Existing work has adequately addressed generality of phenomena across individuals (e.g., expert-novice distinctions, across disciplines), but has often neglected potential generalizability issues across problems (with some rare exceptions, e.g., Chiu & Shu, 2012). Thus, purported effects may be specific to certain kinds of problem contexts, and prior contradictory findings may have come from studying different kinds of problems across studies.

E-trash into real cash
Companies can end up with left-over electronics and components for electronics, imagine if there was a marketplace for them to sell their scrap, trash, and left-over chemicals to other companies that need it.

Example Use cases:
1: Big Corp makes 50,000 widgets that need ingredient A in the casing. Unfortunately, the widgets are discontinued and Big Corp is left with mountains of ingredient A that they don't foresee using the future. They are about to throw it all away since they need the space in their warehouse when Big Corp goes to E-trash.com and finds Fancy Corp who just decided to make 100,000 gizmos that really need ingredient A. E-trash facilitates the transaction and mountains of ingredient A don't go to the landfill!
2: Big Corp has thousands of version 1 doodads that they used for the last couple of years but now they need new version 2. They need to get rid of it quickly and so they go to E-trash.com and put it up to find out that Fancy Corp really needs doodads and version 1 works perfectly! Transaction made! Alternatively, version 1 just isn't applicable anymore but ingredient B in it could be very valuable so through E-trash.com they find a recycler who specializes in extracting ingredient B from old electronics and then selling it to other companies.

Description:
It would be an on-line marketplace for businesses to find business buyers for their large quantities of e-waste. Sellers could post, either publicly or to select partners, what "waste" they have available and then buyers could bid on the "waste" that they could actually use. Lots of e-products and electronic components can be re-used and re-purposed. This would provide a method for companies to make money off of their waste and to find necessary products and components at a discount.

This idea is in large part inspired by the company recyclematch.com. They focus more on traditional manufacturing components.

How does your concept safeguard human health and protect our environment?
It helps to prevent companies from disposing of large quantities of e-waste that other companies could really use.
Where does your concept fit into the lifecycle of electronic devices?
It fits in at the end/beginning of the lifecycle as one business loses the need for the e-waste components or end products that could serve as a foundation point for another company's products.
What steps could be taken today to start implementing your concept?
Encourage existing b2b waste management companies like recyclematch to pursue this by providing the business case of how much money is in working with e-waste especially as the necessary raw materials get harder to find.
What kinds of resources will be needed to fully implement and scale your concept?
Would need an on-line marketplace or perhaps a grant could be awarded to recyclematch or some other player in business to business (b2b) waste management who would already have the necessary connections and framework of a marketplace that could be build upon.

Figure 3: Example concept (text and visuals) to illustrate typical amount of detail per concept

III.B. Data Collection

The target sample for the proposed work will examine 12 completed challenges that involved 4,557 inspirations and 2,344 concepts, posted by 2,452 unique contributors; 5 prior challenges are excluded because they were administered before the “collaboration map” (along with explicit instructions to cite sources of inspiration) feature was introduced.

With administrator permission, all inspirations and concepts, which exist as individual webpages, have already been downloaded, and the following data and metadata was extracted:

1) Concept/inspiration author (who posted the concept/inspiration)
2) Date first posted
3) Applause (how many OpenIDEO users applauded the concept/inspiration)
4) Number and content of comments
5) Outcomes: shortlist status (yes/no), and win status (yes/no)
7) Cited *internal* sources of inspiration (i.e., concepts/inspirations within OpenIDEO)
8) Full-text of concept/inspiration, including (for concepts) answers to challenge questions

Sources of inspiration. In addition to these data (which are already present in the webpage metadata for each concept/inspiration), the following procedures will be followed to calculate each concept’s *conceptual genealogy*. I will derive each concept’s genealogy within OpenIDEO using the “builds upon” links between concepts and inspirations. Specifically, for each concept, I will use a simple algorithm to find all sources that it builds upon, and then find all sources that each of these sources build upon, traversing the conceptual tree to its endpoint. In this way, I will have a record of all contributors to a concept, whether direct or indirect. The gathering of sources will ignore duplicate entries; for instance, if an inspiration I is a direct source for a concept C (at level 1), and also for another concept/inspiration at level 2, we will only count source S once as a level 1 source.

In addition, I will have trained research assistants read each concept and note any *external* (i.e., not from within OpenIDEO) sources of inspiration mentioned in the description. I have a piloted coding scheme ready. It distinguishes between general knowledge and specific sources of inspiration. External sources could be external videos that the contributor watched, or an existing program or application outside of OpenIDEO. An example of this can be seen in the example concept in Fig. 3, where the author mentions being inspired by the company recyclematch.com. The coding scheme reliability is high (k = .8). This coding will likely only be conducted for a representative subset of the data because it is highly labor intensive (estimated 118 man-hours for all 2,344 concepts).

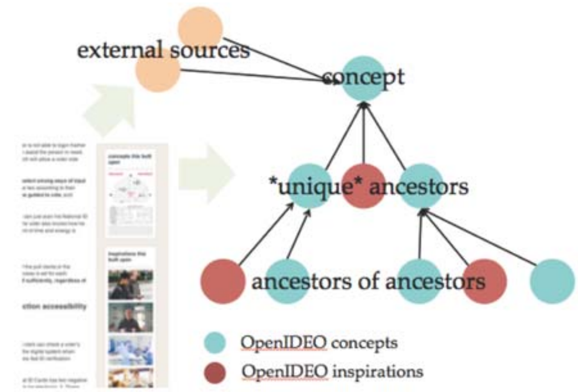

Figure 4: Illustrated conceptual genealogy data structure for each concept

The result of this coding procedure will be a conceptual genealogy for each concept, recording the sources of inspiration (both internal and external) for each concept. Figure 4 illustrates the data structure that will be obtained for each concept.

III.C. Measures

III.C.1. Creative outcomes

The creative outcome measures are *shortlist status* and *win status*. Shortlist status reflects the perceived promise of a “raw idea” (cf. Kornish & Ulrich, 2012), while win status reflects the perceived creativity of the final, “pre-production” version of the concept, analogous in form to final design specifications. Many winning concepts have already gone through some form of prototyping and iteration before they are chosen as winners.

Both measures possess a high degree of validity relative to other more commonly used measures of creative outcomes, such as patent applications/awards or ideation process measures (Shah et al., 2003): as Brown (1989), Amabile (1982) and others have pointed out, the consensus of domain experts is likely to be our best available measure of the creativity of a product. My outcome measures are based on the consensus judgment of domain experts: 1) the challenge sponsors, who have spent significant time searching for and learning about existing approaches, and 2) the IDEO administrators, who are experts in the general domain of creative design, and who have spent considerable time upfront with challenge sponsors learning about and defining the problem space for each challenge. Nevertheless, the administrators’ and sponsors’ involvement throughout each challenge may introduce bias in the selection of shortlisted or winning concepts (e.g., they may prefer concepts that more closely followed their initial ideas at the beginning of the challenge). To estimate the presence/absence/degree of such bias, evaluations of concepts from domain experts outside of OpenIDEO are needed; thus, I will also obtain external evaluations of concepts from domain experts using funds from this grant, for 4 of the 12 challenges.

III.C.2. Primary predictor variables of interest

III.C.2.1. Mean source conceptual distance from domain

The first primary predictor variable will be the mean distance of the sources of inspiration from the working domain. This variable will be measured in a few different ways to help ensure generality, with the following sources of variation: 1) distance measure type, 2) definition of domain, and 3) source set.

Distance measure type. The measurement of conceptual distance (specifically, alternatives to traditional binary measures) is a major methodological challenge in the literature, especially if one wishes to study large samples of ideation processes (e.g., at the scale of the proposed work). Continuous distance measures (ratings of distance between all pairs of concepts) are extremely costly to obtain at this scale, especially if the sources and concepts are naturalistic (e.g., relatively developed text descriptions vs. simple sketches or one-to-two sentence descriptions). Human raters may suffer from high levels of fatigue, resulting in poor reliability or drift of standards. Several computational approaches exist, but it is not currently obvious which automated alternatives are valid and feasible for real problems, e.g., continuous distance metrics based on computational analogy models still require hand coding of propositions for source and target (Forbus, Gentner, & Law, 1994; Taylor & Hummel, 2009). In addition, as detailed in II.A.2, inconsistencies among different binary measures, and between binary and continuous measures, are a potential source of noise in the empirical literature. In response to these challenges, I will employ a combination of human judgments (both binary and continuous) and topic modeling (continuous).

The problem of measuring conceptual distance of sources from the challenge domain and/or individual concepts within a large corpus of concepts and sources is analogous to the problem of understanding the relationship between documents in a large corpus, a problem that has seen much research in the field of machine learning and data mining (e.g., recommending relevant articles to news readers, understanding the topical landscape of large corpus of unlabeled academic articles). Topic modeling (Steyvers & Griffiths, 2007) has emerged as one of the major approaches for solving this problem and is a promising candidate for application to this work's context. Topic modeling techniques treat documents as "bags of words", with the words coming from mixtures of topics, defined as probability distributions over words; given the "bag of words" in each document, they attempt to infer the overall topic distributions over words, and (for each document) the topic mixture that most likely gave rise to the observed "bag of words". A particularly advantageous property of topic models is its assumption of documents as topic mixtures, which aligns with the multi-component nature of design concepts (e.g., each concept often has multiple functional sub-systems); older semantic models like the popular Latent Semantic Analysis method (Deerwester et al., 1990) work best when each document in the corpus is comprised of a single dominant topic (Lee et al., 2010), and clustering techniques also typically assign documents to only one cluster (as opposed to multiple topics; Steyvers et al., 2004).

One key output of the topic modeling process is a re-representation of each document as a sparse vector of topic proportions (which indicates the document's topic mixture, i.e., which inferred latent topics are present and to what degree in each document); with this representation, we can straightforwardly model the conceptual relationships between documents in the corpus using standard information retrieval similarity metrics (such as cosine similarity). Given the size of the dataset for this work (and the potential issues with human ratings for large datasets, as detailed above), this topic modeling approach will serve as the main "workhorse" distance measure for the full dataset, while the human judgments will primarily serve as benchmarks and validation, a necessary step given the relative novelty of the approach and lack of existing validation studies in this context.

Human judgments. Using funds from this grant, concepts will be rated by trained research assistants for conceptual distance from the challenge brief and from each concept using a Likert-type 1-6 scale. To maximized measure reliability, I will employ teams of 5 raters (in pilot work with 5 raters, intraclass coefficients were .75 or greater).

In addition, to address the methodological issue of the diversity of distance measures and increase comparability to existing literature, I will also obtain binary within- vs. between-domain judgments. The current iteration of this measure uses the specific problem being solved (e.g., increasing bone marrow donations, dealing with e-waste) as the domain reference, sorting posts that primarily describe information, existing solutions, and proposed solutions (e.g., concepts) directly addressing the specific problem into the "within-domain" category, and all other posts (e.g., analogous solutions, information) into the "between-domain" category; reliability of the measure in pilot work using two trained raters is encouraging, with Cohen's kappas of .75 or greater.

These human judgments are extremely time consuming and labor intensive (estimated 351 man-hours for estimated 7,032 judgments, assuming 3 sources for each of the 2,344 concepts, and 3 minutes per judgment) to obtain. Further, exhaustive sampling is unlikely to provide significant improvements over representative sampling. Thus, these judgments will only be obtained for 6 of the 12 challenges.

Topic modeling. Two specific topic modeling techniques will be explored: Latent Dirichlet Allocation (LDA; Blei, Ng, Jordan, & Lafferty, 2003), and Correlated Topic Models (CTM; Blei & Lafferty, 2006). LDA uses Bayesian inference to infer topic distributions and document topic proportions, using a Dirichlet distribution for its priors (hence Latent *Dirichlet* Allocation). It is widely used for information retrieval tasks, as well as understanding of the semantic landscape of unlabeled full-text repositories of academic papers (Griffiths & Steyvers, 2004). CTM is a mathematical extension of LDA that allows for modeling of covariance structures among inferred topics by substituting the logistic normal for the Dirichlet prior. It has also been used for modeling of large unlabeled academic repositories (Blei & Lafferty, 2007).

Since it is not obvious from prior work whether LDA or CTM will produce the most valid/useful distance measure in this context (e.g., CTM has the potential advantage of more accurate modeling of inter-document relationship, but its reliance on iterative variational inference methods may lead to biased estimates of topic distributions/proportions relative to LDA; Blei & Lafferty, 2007), I will choose the method that provides the best fit to human judgments. I will also use the human judgments to optimize user-specified parameters for the models (e.g., dealing with frequent/infrequent words, deciding on the number of topics). Both LDA and CTM produce topic-proportion vector representations of documents, which will allow for derivation of similarity measures.

Early validation checks of LDA-derived measures provide a proof-of-concept for the general topic modeling approach: benchmarking the distance measure for inspirations in the e-waste challenge against an aggregate of 5 trained judges' conceptual similarity judgments, the LDA-derived cosine similarity between the inspiration document vectors and the challenge brief document vector correlate with the human judgments at R = .483 (using 750 topics, and all parts of speech, removing stopwords; see Figure 5), an agreement rate equal to the highest agreement between judges. A validation check of LSA using an identical procedure supported the decision to choose LDA and CTM over LSA as primary candidates; the best LSA correlation with human judgments was R = .265.

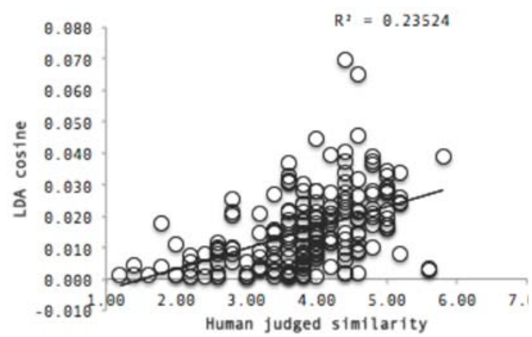

Figure 5: Validation results for LDA-derived conceptual distance measure

Domain definition. The working domain will be defined both in terms of the *challenge brief* and the *concept*. That is, measures of conceptual distance will be obtained separately for sources of inspiration with respect to the challenge brief and concept.

Source set. I will estimate mean conceptual distance for 4 classes of source sets: 1) *immediate* sources, 2) *indirect-recent* (i.e., depth 2 to 4 in genealogy), 3) *indirect-medium* (i.e., depth 5 to 7 in genealogy), and *indirect-old* (i.e., depth 8 or greater in genealogy). This variation in source sets can support exploration of finer-grained hypotheses about the effects of source conceptual distance. For instance, far sources may come with an attendant cost (e.g., lack of fit, effort required to map); however, if a concept author accesses "ideation material" from far sources *through* some other concept/inspiration, s/he might be able to benefit from those far sources without paying the costs. Thus, there might be a smaller benefit of distance for immediate sources, and a larger benefit of far sources deeper in the genealogy.

III.C.2.2. Mean source conceptual diversity

The second primary predictor variable will be mean source conceptual diversity. This measure will be derived from the topic modeling cosine similarity measures. Specifically, I will estimate the mean pairwise cosine similarity between sources of inspiration (whether concept or inspiration), as given by the topic modeling measure. This measure will also be derived for 4 levels in each concept's genealogy: 1) *immediate* sources, 2) *indirect-recent* (i.e., depth 2 to 4 in genealogy), 3) *indirect-medium* (i.e., depth 5 to 7 in genealogy), and *indirect-old* (i.e., depth 8 or greater in genealogy).

III.C.3. Control measures

Given the observational design, it is important to account for major factors that may influence the creative outcomes of concepts (particularly in the later stages, where prototyping and feedback are especially important) and may be correlated with the predictor variables. The following control variables will be used: 1) amount of feedback, 2) quality of cited sources, and 3) author effects.

Feedback. Given the collaborative nature of OpenIDEO, feedback in the form of comments will likely turn out to be important. Comments can offer encouragement, raise issues/questions, recommend additional sources of inspiration, or provide specific suggestions for improvement. These types of feedback have the potential to significantly enhance the quality of the concept. Further, feedback may be an alternate pathway to success via source distance, in that concepts that build on far sources may attract more attention and therefore higher levels of feedback, which then improve the quality of the concept; failing to account for feedback may lead to inflated estimates of the effects of source distance.

Two versions of the feedback variable will be derived: 1) number of comments pre- refinement (*pre-refinement feedback*), and 2) amount of feedback post- refinement (*post-refinement feedback*). Pre-refinement feedback will serve as a control for estimating the effects of the predictor variables on shortlist status, while post-refinement feedback will serve as a control for estimating the effects of the predictor variables on win status.

Quality of cited sources. Concepts that build on high-quality concepts (e.g., those who end up being shortlisted or chosen as winners) have a particular advantage of being able to learn from the mistakes and shortcomings, good ideas, and feedback in these high-quality concepts. Thus, the number of shortlisted or winning concepts a given concept builds upon could be a large determinant of a concept's success; omission of this predictor might lead to poor model fit and underestimation of the effects of the primary predictor variables.

Author effects. Contributors may vary in terms of design expertise, as well as familiarity with the OpenIDEO platform. Setting aside the issue of nature/nurture, there are clearly stable differences in observed creativity between individuals. This has been attributed to, among other things, personality (Batey & Furnham, 2006), and working habits, specifically fluency of output (Simonton, 1997). In addition, while experts are known to be more adept than novices at crossing conceptual boundaries when using inspiration sources (Bonnardel & Marmèche, 2005; Goldschmidt, 2001; Novick, 1988), it is not clear to what extent this is an *effect* of their deeper knowledge structures or a *cause* of their superior performance. Thus, apart from accounting for a potentially large amount of variance in creative outcomes, author expertise might also be a confounding variable.

I do not have access to personality measures, but I do have some record of fluency of output within OpenIDEO. Thus, I will include overall fluency of output (number of posted concepts across challenges as a control variable for author effects).

III.D. Analyses

Quantitative analyses. The research questions in the overall proposed work will be primarily investigated using a multilevel modeling approach. Given our interest in observing the effects of source use patterns on concept outcomes, and the nesting of these concepts within authors, **failing to account for such nesting effects would overestimate the statistical significance of model estimates (i.e., make unwarranted claims of statistically significant effects)**. This issue is exacerbated if the effects being tested are likely to be relatively small, as is likely the case here. Thus, I will be estimating a series of 2-level hierarchical logistic regression models, with 2,344 *concepts* at level 1, nested within 1,109 *authors* at level 2.

The level-1 model is expected to be:

$$Y_{ij} = \pi_{0j} + \pi_{1j}(SDIST1) \ldots + \pi_{4j}(SDIST4) + \pi_{5j}(CDIST1) \ldots + \pi_{8j}(CDIST4)$$
$$+\pi_{9j}(FEEDBACK) + \pi_{10j}(QPRIOR) + e_{ij}$$

where

Y_{ij} is the probability of being shortlisted (or winning) for concept i of author j;
π_{0j} is the mean probability of being shortlisted (or winning) for concepts of author j;
$\pi_{1j}(SDIST1) \ldots \pi_{4j}(SDIST4)$ are the estimated effects of mean source distance for each of the 4 levels in the genealogy (*immediate, indirect-recent, indirect-medium, and indirect-far*);
$\pi_{5j}(CDIST1) \ldots \pi_{8j}(CDIST4)$ are the estimated effects of mean conceptual diversity for the same 4 levels;
$\pi_{9j}(FEEDBACK)$ is the estimated effect of feedback for the concept;
$\pi_{10j}(QPRIOR)$ is the estimated effect of the number of shortlisted or winning concepts in the concept's genealogy; and
e_{ij} is the random "concept effect", i.e., deviation of concept *ij's* score from the cell mean.

The level-2 model is expected to be:

$$\pi_{0jk} = \theta_0 + b_{00j} + \beta_{01j}(QUANT)$$

where

θ_0 is the grand-mean probability of being shortlisted (or winning) among all concepts;
b_{0j} is the random main effect of author *j*; and
$\beta_{01j}(QUANT)$ is the estimated fixed effect of the author *j*'s fluency of output

The estimates for $\pi_{1j}(SDIST1) \ldots \pi_{4j}(SDIST4)$ address Research Question #1 (source conceptual distance), and the estimates for $\pi_{5j}(CDIST1) \ldots \pi_{8j}(CDIST4)$ address Research Question #2 (conceptual combination distance). Interactions between $SDIST$ and $CDIST$ effects will also be explored once stable parameter estimates for their independent effects have been established (in order to prune the large space of possible interaction terms). I will not be explicitly modeling potential challenge-level variation due to statistical power considerations: the N is only 12, and it is known that small sample sizes at level 2 render estimates of the variability of level-1 slopes across level-2 units untrustworthy (Scherbaum & Ferreter, 2008; Snijders, 2005). I will, however, explore potential generality across challenges by estimating separate models within each challenge, and note any observed variability for future work with better statistical power. While the average cell size at level-2 for authors is low (on average approximately 2-3 concepts per author, and many singletons), these are not a significant concern for estimates of fixed effects at level-2, which are the primary hypotheses of interest with respect to author effects.

Case studies. In addition to the multilevel models, case studies will also be conducted for representative concepts in the dataset. The focus of these case studies will be to examine the ways in which source distance and diversity contribute to the quality of each concept. This qualitative data will supplement the insights gleaned from the quantitative modeling and ground inferences drawn from those results. Triangulating the quantitative and qualitative data may yield more insights about the nature of the cognitive mechanisms underlying any observed relationships, and will help reduce concerns about spurious statistical relationships.

IV. EXPECTED OUTCOMES AND BROADER IMPACTS

The proposed work will lend significant insight and clarity to the question of how to curate and use sources of inspiration in the creative process. Broader impacts can be expected for both the science and practice of creativity and innovation. From a theoretical perspective, failure to support the hypothesis that far sources or combinations benefit more than near ones in a context with high statistical power, external validity, multiple distance measures and design problems, and realistic time scale would provide impetus for re-examination of the theory of source conceptual distance and its relationship with creative outcomes. Alternatively, strong support for the far source and combination hypotheses would help to solidify theoretical notions of the unique benefits of far sources. Methodologically, the validation work for the topic modeling approaches — especially the explicit comparisons with binary within- vs. between-domain measures, and examination of possible systematic variation in effects by distance measure type — will help point other creativity researchers forward towards convergence of measures, potentially helping to reconcile conflicting results and spur theoretical progress.

For creative practice, the most obvious connection is to research and development of computational support tools for retrieving and using sources of inspiration in the creative process. Such tools are an active area of research, particularly in engineering design methodology (Bohm, Vucovich, & Stone, 2005; Chakrabarti et al., 2005; Duflou & Verhaegen, 2011; Fernandes et al., 2011; Fu et al., 2013; McAdams & Wood, 2002; Shneiderman, 2000). In the design of these tools, the questions of what kinds of sources to retrieve, and how to present them to the practitioner, are fundamental issues to address. Should these tools retrieve only highly relevant sources? Or perhaps include some far sources? Or mostly far? Should results of retrieval requests be shown with other similar sources, or in conceptually diverse sets? Fine-grained answers to these questions (beyond simple near/far, as research with continuous measures, such as the proposed work will employ) can ultimately lead to the design of more effective supports for creative practitioners. From the client side, too, insights gleaned from this work could support the design of user guides for such support systems, governing effective ways one might *select* candidate sources returned by such systems. These implications are also relevant for the design of innovation platforms such as OpenIDEO, Quirky, and Innocentive, which are becoming increasingly important sources of innovation, to help ensure that contributors interact with each others' ideas in a way that inspires rather than harms innovation. To ensure transfer of insights, I will present the results of this work at venues frequented by designers and users of innovation support tools and innovation platforms, such as the American Society of Mechanical Engineers' Design Theory and Methdology conference, and the Association for Computing Machinery's Computer-Supported Collaborative Work conference.

Additionally, this work could have significant impact on creative practice more broadly. A common belief among practitioners is that far sources and combinations are more beneficial for creativity; if either of these beliefs turn out to be false, unnecessary setbacks and slowdowns of innovation can be avoided by addressing those erroneous beliefs. Relatedly, an accurate understanding of best practices for curating sources of inspiration is a critical foundation for training the next generation of creative practitioners. I will leverage existing connections with industry practitioners (e.g., the innovation consulting firm InnoSight, affiliated with Dyer, Gregersen, & Christensen, 2011) and engineering and design education (both at the University of Pittsburgh and Carnegie Mellon University) to work towards actionable knowledge transfer and foster increased connection between research and practice of creativity and innovation. Looking forward, insights gleaned from this work (and other similar tandem *in vivo*/*in vitro* lines of research) could also be integrated into a central repository describing evidence-based "best practices", similar to evidence-based medicine (Dickersin, Straus & Bero, 2007), or the Institute for Education Sciences' "What Works ClearingHouse" initiative (http://ies.ed.gov/ncee/wwc/). Overall, sharing insights from this work with practitioners will not only have potential transformative impacts on creative practice, but will also yield useful ideas for further investigations that, together with the results of this work, will advance the scientific basis of innovation practice and policy.

V. SCHEDULE

The proposed work is expected to run over the course of approximately 6 months, beginning in the summer (early May), and ending in November of 2014 (see Fig. 6). The dissertation defense will be scheduled for late November or early December, at latest. Funds are needed beginning in May.

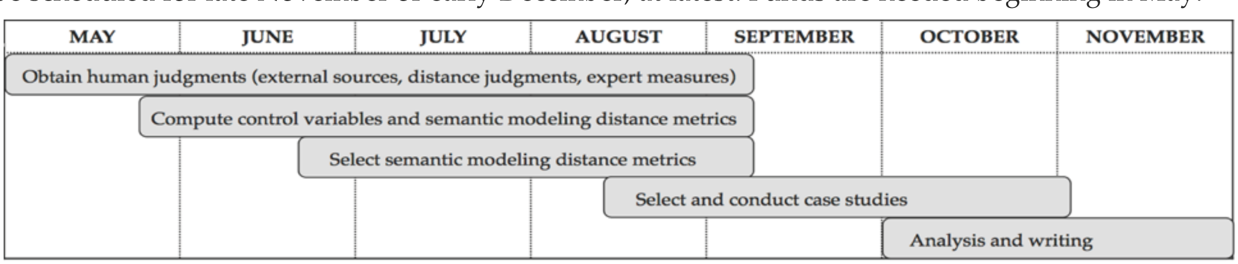

Figure 6: Expected timeline

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