An Exploratory Study about the Role of Ambiguity During Complex Problem Solving

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Abstract

The concept of ambiguity is often discussed within the field of Artificial Intelligence; however, its role and effect on early-stage complex problem solving is not well understood. This paper describes a theoretical framework that recognizes the relationship between ambiguity and uncertainty, as these variables change throughout the different stages of problem solving. We particularly focus on the start of the process, when ambiguity and creativity are typically high. Through a case study approach, we hope to provide a foundation for the design and development of creative intelligent systems that more effectively support ambiguity during complex problem solving.

Keywords: ambiguity, uncertainty, creativity, complex problem solving, system design

Introduction

It has long been recognized that ambiguity is a dominant characteristic in complex problem solving. Although technical managers and designers aim for clarity and precision in their final solutions, the problem-solving process often retains levels of ambiguity from the start. Since ambiguity can occur or re-emerge at any stage, it is important to understand how ambiguity levels fluctuate and affect participants' creativity output throughout the process, since this knowledge directly informs the development of creative intelligent systems for real-world use (Reddy 1996; Buchanan 2001).

Theoretical Framework

The concept of ambiguity is prevalent across multiple fields and is often discussed in the processes of creativity, decision making, and complex problem solving. Although each field interprets ambiguity slightly differently, an initial analysis reveals several interesting themes. Relevant to this paper, a shared definition of ambiguity did not exist, and there was mixed opinion about how ambiguity is measured depending on the situational context and the accepted methods in respective fields. Furthermore, ambiguity was sporadically interchanged with uncertainty as comparable terms. Essentially, ambiguity is the condition of "unknown unknowns", which is defined by the state of not knowing what to measure, how to structure any measurements, or possibly even where to start looking for variables. In contrast, uncertainty is defined as "known knowns", which is the state in which variables are identified, although the parameters may be incomplete, insufficient or imprecise.

Research in Artificial Intelligence generally considers ambiguity from the perspective of the system. As most systems are fundamentally based on deduction, AI researchers have historically grappled with the concept of ambiguity as an incomplete or non-closed set of propositions (De Luca and Termini 1977; Watanabe 1987; Sarma, 1994; Wang and Wong, 1994). While not defined as a technical term, ambiguity is often discussed as an explicitly stated, defining requirement of intelligent systems. In particular, Reddy (1996) states that intelligent systems should be designed to "tolerate error and ambiguity in communication" (p. 86), and multiple studies involving ambiguity and intelligent systems have largely concentrated on areas related to word recognition, semantics, and fuzzy logic (Feigenbaum 1977; Church and Patil 1982; Resnik 1999; Zadeh and Kacprzyk 1999). However, few studies have addressed the limitations inherent in AI systems for supporting complementary problem-solving processes of abduction and inductive evaluation (Watanabe 1987).

Subsequently, we looked to other domains to help address this gap and better understand the role of ambiguity during early-stage complex problem solving. Multiple studies in the field of Creativity examine the activities and practices that occur at the start of the ideation process – a time discussed under multiple related names, including: conceptualization, discovery, problem finding, problem forming, problem framing, pre-inventive, pre-ideas, idea formation, need-finding, and incipient innovation (McKim 1972; Simon 1995; Finke, Ward, and Smith 1992; Amabile 1996; Sternberg 1999; Adams 2001; Lubart 2001; Cockayne 2004). Although ambiguity was often noted as a key characteristic of the creative process, there was limited analysis of the strategies employed by individuals or teams to handle ambiguity, especially in relation to complex problems.

Related studies in the fields of Product Design and Communication show that teams often actively use ambiguity to negotiate intended meaning, notably as problems are identified and further refined (Festinger 1962; McLuhan 1967; Schön 1983; Minneman 1991; Simonin 1999; Stacey and Eckert 2003; von Stamm 2003; Aoki and Woodruff 2005; Cross 2006). Broadly speaking, ambiguity is regarded as a positive and active element in a group process. In addition, the notion of complex problems regularly surfaces in Design studies and was originally characterized in the 1960s as "wicked problems" since these problems were considered fundamentally intractable (Rittel and Webber 1973).

Management Studies provided the remaining data in our literature review. In a seminal piece, Schrader, Riggs, and Smith (1993) define ambiguity during times of technical problem framing and solving in a business framework. They characterize uncertainty as a lack of information and ambiguity as a lack of clarity about a problem at hand. Ambiguity is perceived in regard to the relationship between the variables and the problem-solving algorithm. As they explain:

> The set of assumed relationships between variables reflects the problem solver's understanding of the structure of the problem. The problem-solving algorithm relates to how this understanding is to be used for problem solving. (p. 78)

Two levels of ambiguity are defined based on the variables and functional relationships involved:

> **Uncertainty.** Characteristic of a situation in which the problem solver considers the structure of the problem (including the set of relevant variables) as given, but is dissatisfied with his or her knowledge of the value of these variables. (p. 77)

> **Ambiguity level 1.** Characteristic of a situation in which the problem solver considers the set of potentially relevant variables as given. The relationships between the variables and the problem-solving algorithm are perceived as in need of determination. (p. 77)

> **Ambiguity level 2.** Characteristic of a situation in which the set of relevant variables as well as their functional relationship and the problem-solving algorithm are seen as in need of determination. (p. 78)

They stipulate that problem solvers deliberately choose the levels of uncertainty and ambiguity based on the process and situation. Specifically, people use mental models to approach and solve problems. When ambiguity is high, problem solvers "must find or create an appropriate model as part of the problem-solving process" (p. 77), which then helps determine the requisite tasks, inputs, and desired outcomes. Schrader, Riggs, and Smith developed an Uncertainty-Ambiguity Matrix to show how problem solvers approach different stages of the same problem along the axes of uncertainty and ambiguity, which is reproduced in Figure 1. Decisions are made based on three key factors: (a) prior problem-solving experiences, (b) organizational context, and (c) available resources. They discuss sixteen propositions for determining a person's response to uncertainty and ambiguity throughout the problem-solving process using these factors.

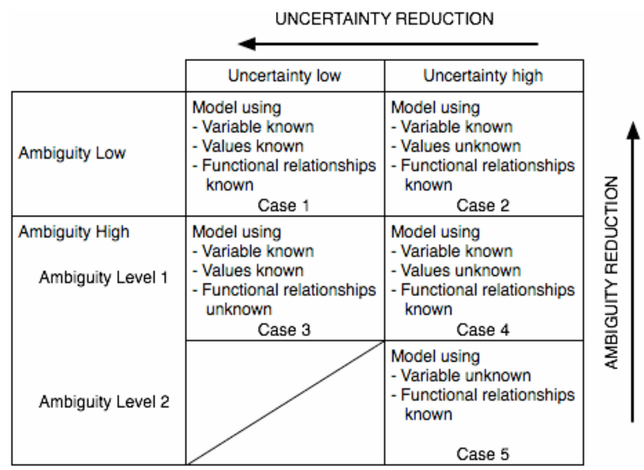

Figure 1. Uncertainty-Ambiguity Matrix (Schrader, Riggs, and Smith 1993)

Methodology

Our research into ambiguity began at Stanford University as part of industry-sponsored design research in the late 1980s (Minneman 1991). This research program, conducted in conjunction with the award-winning course ME 310 Design Entrepreneurship, has been run with the mantra "Preserve Ambiguity," a concept that been adopted by additional design and innovation programs across the university and abroad. This applied understanding of ambiguity laid the general foundation for our methodology.

As a continuation of this research program, we conducted a multi-day workshop in India. Our sample (n=28) was comprised of senior engineering research managers working with technology and manufacturing companies in India. Each of the companies is considered a leader in its respective industry, delivering an array of complex products – including tractors, industrial pump systems, home appliances, turbines, power generators, pressure and temperature instruments, and automobiles – for Indian and international markets. Over a third of the subjects lead global product teams and have spent extensive time outside of India for schooling and work, so they had a broad international perspective.

Our objective was to explore how technical managers approach early-stage complex problems that begin with high levels of ambiguity. The workshop theme was "movement in megacities in 2025", which offered an open-ended, complex framework in a controlled setting. This theme was selected because India currently has two of the top five megacities in the world, ensuring that our sample had a baseline familiarity with the issues inherent in megacities.

The participants, all male and mid-aged, were grouped into seven teams. Each team selected members based on company alliances or similar interests, and teams choose their own topics based on the workshop theme, such as the complex problem of transporting farm goods into megacities or the problem of household water supply, delivery, availability, use, and re-use in the future. By starting with both organizational and topical self-selection, our goal was to remove early sources of conflict and focus participant energy on collaboration and problem solving.

Complex Problem-Solving Process

While self-defined topics were different across teams, the problem-solving process was consistent. All participants were taught six distinctive critical thinking models during the first two days and encouraged to apply these models throughout the workshop. These models were selected from methods used extensively in Stanford engineering undergraduate and graduate courses and corporate workshops (Cockayne 2007). These methods are briefly summarized below.

A. S-curve analysis. A graphical representation to explain the progression of changes in terms of technological, social, and other related filters.

B. Janus cones. A foresight framework for looking backwards and forwards in time to identify the timing of historical events and how these timings affect similar future events within an opportunity space.

C. Daisygram. A mapping technique for capturing emergent conversation themes in complex problems.

D. Design skit. A short theatrical performance to illustrate a particular user need or design benefit.

E. 3-D paper prototyping. A design method to build and communicate a product concept in three-dimensional space by using paper and other inexpensive materials.

F. Dark horse prototyping. A design method to build and communicate a product concept that is considered high risk and/or least likely to succeed.

We designed the workshop to take participants on a journey from high to low ambiguity in three distinct phases: Foresight, Research, and Design. This plan allowed participants to become more comfortable with ambiguity as a precursor to being creative. During the Foresight phase, participants used the first three methods (A, B, C) to decide how best to approach their workshop topic, with teams choosing their own preferred mix of prescribed methods. During the Research phase, participants gathered data from credible sources and reworked their problem solving models to either update earlier thinking or to better present newly collected data (A, B, C). Finally, during the Design phase, teams used each of the last three methods (D, E, F) to bring their topics to life, and after hearing from each other, they iterated prototypes and often chose to update earlier models again (A, B, C). Team presentations occurred once at the end of the Foresight phase, once at the end of the Research phase, and twice during the Design phase. The last presentation segued into group reflections and learnings from the overall problem-solving process.

All presentations and workshop instructions were recorded, and every team artifact and prototype built was photographed. Feedback was solicited from participants throughout the process via multiple informal interviews. In addition, several senior faculty and advanced graduate students served as participant-observers and provided additional feedback and notes.

Discussion

With these results, we initially applied the theoretical framework from Schrader, Riggs, and Smith, since it offered the most pertinent description of ambiguity in a problem-solving context. We can confirm the change from high to moderate ambiguity throughout the workshop as a determinant of the participants' perceived ability to solve complex problems. Most telling, overall team moods were tense during the first two presentations, since participants did not know which variables to identify, how these variables might fit the problem solving models provided, and what the underlying problem structure entailed. This feeling of tension was palpable and was recorded through self-reporting and observation. By the final presentations, teams ultimately reported high satisfaction with the process and the outcome, even remembering their earlier bouts of frustration as a valuable part of the learning.

Analysis of Related Propositions

Using the Uncertainty-Ambiguity Matrix from Schrader, Riggs, and Smith, we focused on the three categories underlying their multiple propositions. These categories describe the factors affecting how people handle ambiguity during problem solving: (a) prior problem-solving experiences, (b) organizational context, and (c) available resources, and according to Schrader, Riggs, and Smith, the combination of these factors indicates a strong tolerance for situations of high ambiguity. Our analysis pertains to the workshop and was informed primarily through user-reported data, participant observations, and team artifacts.

Prior problem-solving experiences. As we observed, daily life in India is filled with ambiguity, leading to the development of high levels of tolerance. At the same time, the educational system instills exemplary analytical thinking and problem-solving skills, and as one participant noted: "In India, we are taught to remove ambiguity". These two capabilities for dealing with street life chaos and workplace order are often described as being diametrically opposed and irreconcilable; however, all participants proved this assumption to be false. In addition, many participants had prior experience living in megacities and facing open-ended problems in industry, but they had little knowledge about specific problem-solving models to use during periods of high ambiguity. Since they did not typically address long-term issues (beyond five years into the future) in their work, they were initially uncomfortable looking beyond that timeframe, and this factor contributed to high levels of ambiguity within the workshop. Based on the strong results delivered by each team and the positive experience reported at the end of the workshop by all of the participants, we surmise that they will likely approach future problems containing high ambiguity with much greater willingness and ability.

Organizational context. The workshop was conducted in a controlled setting that proved favorable for exploring the second proposition category of organizational context. The offsite location away from corporate offices helped to enhance team creativity and remove daily organizational constraints. Participants felt empowered to think creatively since their respective companies supported their participation in the workshop. Participants also chose to retain their corporate connections and requested colleagues as teammates. This decision helped to manage ambiguity, since participants gained a shared enterprise language and common project experiences within each team. We believe that participants preferred to maintain organizational roles as a way to cope with ambiguity and solve problems together using familiar algorithms. It also allowed them to take their insights back to each company as a common experience. We suggest additional research to investigate the effect of organizational roles that either help reduce or preserve ambiguity during early-stage problem solving.

Available resources. Turning to the third proposition category, resources were readily available in terms of information, expertise, and personal character. An onsite library and internet access provided access to information during the Research phase, although participants expressed initial uncertainty with new data sources outside their immediate industry area. In addition, the instructors served as process experts throughout the workshop exercises, which helped to reassure participants. Schrader, Riggs, and Smith noted that the availability of "non-solution-specific resources and skills", such as money or time, is a prerequisite for pursuing more novel approaches (p. 88). We applied this principle during prototyping, encouraging liberal use of available materials, and results from each team exhibited high levels of novelty and creativity. Lastly, we found support that some participants personally embraced change more easily than others, and their positive attitude and open mindedness helped to influence those around them.

Extending the Uncertainty-Ambiguity Matrix

While the general propositions proved true in our study, we encountered several challenges applying the Uncertainty-Ambiguity Matrix. We recommend several changes to extend this model for greater application for complex problem solving.

Ambiguity before uncertainty. We did not see instances that combined low uncertainty and high ambiguity about the same problem. Until general ambiguity was reduced to a level at which key variables began to emerge, teams did not have the ability to pursue even questions with high uncertainty. Ambiguity continued to exist throughout the life of the problem, as teams converged on an optimal solution, as shown in Figure 2. This two-step process – first ambiguity, then uncertainty – is further supported from our earlier studies. In addition, our findings did not support two separate levels of high ambiguity since participants' understanding of variables frequently changed during periods of high ambiguity. For example, while some participants felt they understood which variables were sufficiently important at the start of the problem, they revised their assumptions as they gained more information during the next phase.

Measuring ambiguity over time. While the Uncertainty-Ambiguity Matrix helps compare key characteristics of static ambiguity, it does not show the ebb and flow in ambiguity during the development and life of a problem. Instead of a 2x2 matrix, we propose using a graph as illustrated in Figure 2, where time is represented along the x-axis. This format is being tested as a way to record fluctuating levels of ambiguity over time and better understand the early stages in problem solving.

Ambiguity curve. Our data showed a clear change in ambiguity, where there was an overall reduction from high to low throughout the workshop. The change in ambiguity is noted by an Ambiguity Curve in Figure 2, and this curve could change based on the nature of the problem (Cockayne and Carleton 2008). In practice, the curve is not this tidy, since multiple mini-iterations may occur along this path as smaller questions arise and are then solved by a team as they address the greater context of a problem.

Problem finding and defining. Problem solving is often approached as an undifferentiated process without additional steps or sub-processes. In our case, the highest levels of ambiguity occurred at the beginning of the entire process, when each complex problem was highly undefined. This time correlates with early-stage creativity, when problem finding and problem defining are recognized as common activities preceding problem solving. These early stages can be added to the timeline to show additional development from pre-concept to solution, as shown in Figure 2. We also overlaid the three phases of Foresight, Research and Design from the workshop, which participants understood as recognized industry practices for innovation and are often highly segregated within most organizations. While drawn as separate phases, in practice there is evident overlap between each phase.

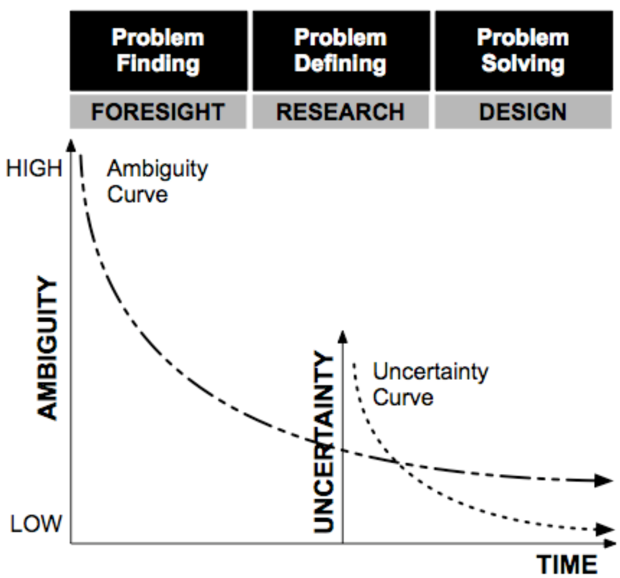

Figure 2. A Broader Spectrum of Complex Problem Solving

Implications for Creative Intelligent Systems

According to Buchanan (2001), the AI community has developed a strong handle on heuristic search with respect to problem-solving models, as well as gained an increased understanding of creativity models and substantial more computing power within recent years. Using the extended framework proposed here, creative intelligent systems should be capable of supporting both ambiguity and uncertainty throughout the different stages of complex problem solving. When new thinking or new models of thinking are needed, additional or better sources of creativity becomes essential to advance between the stages. Human creativity relies on organized patterns of information and experience, which raises challenges for AI system designs. Many systems today can handle increasing uncertainty at the data level; however, it is incumbent on the system designer (or user) to correctly predetermine the context, boundary and goal of the problem. Correctly designing for ambiguity remains an obstacle for AI, and system designers are becoming further aware of the limits of creative intelligent systems, when ambiguity about the problem at hand persists – and may potentially need to be preserved within the data as ideas are iterated and refined.

As the field of AI continues to address complex problem solving, we feel that one of the next hurdles will be to effectively support early-stage activities and extend human capabilities in new areas by recognizing the role ambiguity plays in human cognition. Potential applications for creative intelligent systems may include finding more original and novel ways for resolving ambiguity earlier, providing additional models to more effectively facilitate problem finding and problem defining when ambiguity is high, and augmenting early-stage team activities to either reduce ambiguity more rapidly or manage ambiguity more comfortably.

Further Research

Several limitations exist in our study. First, our sample is small and biased. The workshop participants provided a convenience sample and were not selected to represent normal problem solvers. All participants are highly accomplished in senior roles and were sponsored by their companies based on their prior work in engineering innovation, which leads us to believe that each person had a recognized aptitude for change and strong skills in complex problem solving. Moreover, while we did not directly observe any cultural factors from Indian business that influenced team interactions and problem-solving approaches, additional research might examine how different cultures perceive ambiguity and its effect on complex problem solving and creativity.

In addition, the scope of the study was exploratory, so significant research is needed to further investigate the role of ambiguity in creative intelligent systems and other industrial applications, including design and innovation. Additional studies could examine how ambiguity levels change, as groups refine their problem solving methods over more extended timeframes. We recognize that this study may raise more questions than it addresses, and we hope it contributes to the broader discussion about the role of ambiguity in complex problem solving and creativity support tools.

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