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Understanding and addressing complexity in problem solving

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ABSTRACT
Complexity manifests itself in many ways when attempting to solve different problems, and different tools are needed to deal with the different dimensions underlying that complexity. Not all complexity is created equal. We find that most treatments of complexity in problem solving within both the statistical and quality literature focus narrowly on technical complexity, which includes complexity of subject matter knowledge as well as complexity in the data access and analysis of that data. The literature lacks an understanding of how political complexity or organizational complexity interferes with good technical solutions when trying to deploy a solution. Therefore, people trained in statistical problem solving are ill-prepared for the situations they are likely to face on real projects. We propose a framework that illustrates examples of complexity from our own experiences, and the literature. This framework highlights the need for more holistic problem-solving approaches and a broader view of complexity. We also propose approaches to successfully navigate complexity.

KEYWORDS
Decision making; problem solving; Six Sigma; statistical engineering; statistics

Introduction

Organizations around the world have many problems to solve. These problems range from simple to broad and complex. The complexity that arises from problem solving can appear in many ways. It is crucial to recognize these different types of complexity to be able to correctly address them in problem solving. A recent online article (Guy 2020) noted: “I am talking with the data scientists, who are showing me the clever machine learning models they developed with more than 90% accuracy and complaining that the business people are ignoring their models and prefer to use their old manual process.”

To illustrate what happens when complexity is not recognized, consider the experience of one of the authors (Willis) earlier in their career. Fresh out of school in a new job, he was asked to join a process improvement team for a manufacturing plant. This diverse, small team was composed of several capable individuals with a high level of experience in the tools for process improvement, including the plant leader. As a result, there was strong leadership support and a clear mandate to solve the problem of low yields in the plant. Financial analysis suggested that even a small improvement in the yield could result in significant savings. The goal was clear, and a good team was put together that knew how to use the tools, so success was assured, right?

On the contrary, after a few months of work, the team was disbanded with no demonstrable improvements or financial benefits realized. Why? There were several factors. First, the team found it difficult to get the necessary data that would allow them to diagnose some of the root causes for low yields. There was yield data for different process steps but no other systems in place to easily track the measurements of the process variables. Obtaining the right data turned out to be much more complicated than anticipated.

Second, all the team members had roles outside the project team and over time, priorities on other projects got in the way of the work that the process improvement team was able to do. Managing the requirements of multiple projects also proved complex. Finally, there were a lot of great improvement ideas that resulted from discussions with those who were most experienced with the process. However, the amount of work necessary to implement some of these solutions was more than anticipated. Some of the solutions needed the cooperation of multiple manufacturing teams to implement across the full manufacturing process and the team was not able to deploy those solutions. The organizational complexity, not anticipated initially, turned out to be a barrier to progress.

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This article has been corrected with minor changes. These changes do not impact the academic content of the article.

As a second example, another author (Roger) spent several years early in his career at the now-defunct Scott Paper Company. For the first several years, he led an initiative to deploy statistical process control (SPC) and experimental design (DOE) methods across Scott's US paper mills. He organized a high-level, cross-functional core team to plan the effort, communicated this plan extensively with leadership at each paper mill, and arranged for top-notch technical training of the resources who would lead the deployment at individual mills. Further, he maintained a close network of these resources to share experiences and best practices during deployment. Several positive case studies resulted, which had significant financial impact. However, after about four years, it became clear that no fundamental change in how the paper mills were operated, nor in their financial results, had occurred. What went wrong?

With hindsight, Roger was naïve about the complexities of deploying a major initiative across an organization. He was ignorant of the political environment at the leadership levels of Scott Paper, and how complex some of the relationships were. For example, the initiative was championed by a middle manager, Roger's boss, and other managers quickly picked up on the fact that this initiative was more "optional" than those being driven by senior leadership. While they were cooperative and allowed their employees to participate in training efforts, some had no real intention of actually utilizing these trained employees to drive improvement. Some did not believe SPC or DOE would produce improvement, and all were struggling with limited resources and more initiatives than they could handle. Something had to give. One openly stated that providing people for training was a means of getting their "tickets punched." In short, the overall failure of the effort had nothing to do with the technical complexities of applying SPC or DOE; where these were utilized, positive results poured in.

A more successful case study, which illustrates how some of these issues can be successfully addressed, will be presented below. Our goal in this paper is to highlight different types of complexity illustrated in these three examples. We provide a framework for understanding these different types of complexity. Within the framework, we describe its elements as well as some of the tools that can be used to address complex problems.

Complexity framework

Before we provide a framework for understanding complexity, we start with a definition of what we mean by complex problems. An apt description of the different kinds of problems comes from Gawande (2011), who described 3 major categories of problems. *Simple problems* involve a known recipe that you can follow, such as baking a cake. This would be akin to a flowchart that tells you which statistical method you need to use for a specific type of dataset. *Complicated problems* are much more challenging, such as sending a rocket to the moon. However, complicated problems often can be broken down into a set of simple problems. It takes a lot of knowledge and skills, often from many people. But once you have solved the problem once, it is much easier to do it a second time and replicate the success because the laws of physics do not change. The process to do it can be improved over time. This would be analogous to many process improvement projects. Once you have figured out how to maximize the yield for a manufacturing process, it becomes easier to do that for other similar processes.

Conversely, *complex problems* are described as analogous to raising a child. No wise parent would claim that what works in raising one child works for all children. Each child has a unique personality and a different set of methods and techniques are needed. While there are some general principles of child raising that can be useful, there is no recipe to follow. Success with one child in no way guarantees success in raising another child. Human behavior is much more unpredictable than the laws of physics!

A similar description of different types of problems was elaborated by Pidd and Woolley (1980) and Woolley and Pidd (1981). They discern four types of problems, ranging from straightforward and well-structured to complex and ill-structured:

1. *Checklist Problem Solving*, where the goal is unambiguous, as is the problem analysis process, which follows a stepwise procedure.
2. *Definition Problem Solving*, where the problem is framed in the template of a mathematical modeling problem, in which a solution is derived from modeling and optimizing relationships between variables.
3. *Science Research Problem Solving*, where the problem solving resembles scientific research, with emphasis on empirical fact-finding to discover the real problem.
4. *People Problems*, where the problem is highly subjective and depends on personal values and perceptions; negotiation and reconciliation are important elements of problem solving.

De Mast and Lokkerbol (2012) discuss relevant themes in the scientific literature on problem solving,

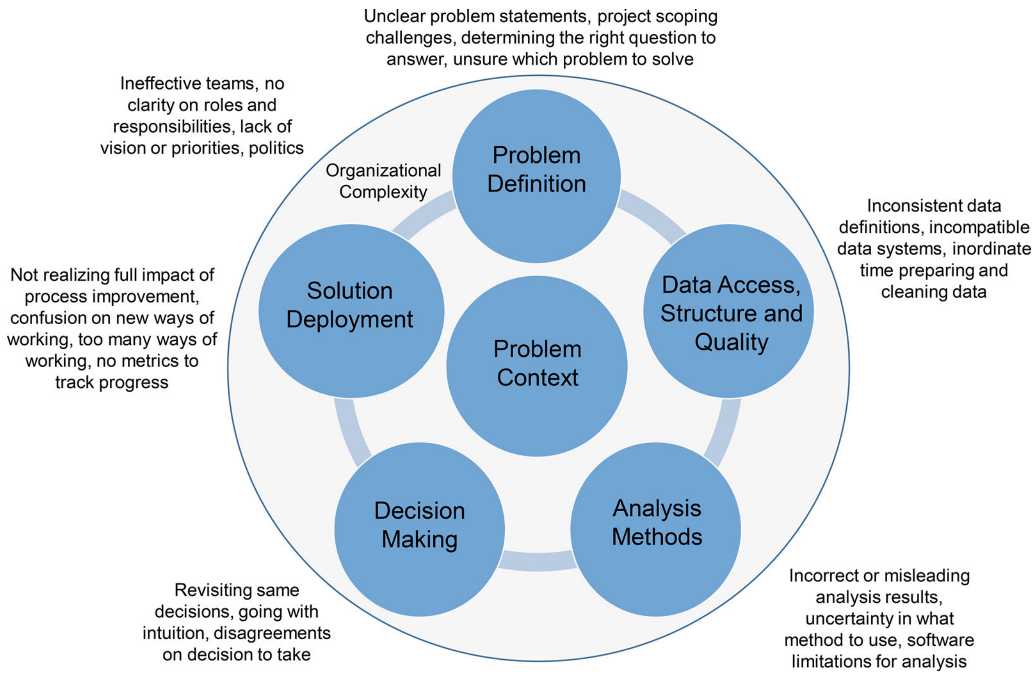

Figure 1. Framework for complexity in problem solving.

relating them to problem solving in quality engineering and Six Sigma. They note that the field of quality engineering has traditionally focused on problems of medium complexity (types 2 and 3 above). Many Six Sigma projects, for example, are examples of *Definition Problem Solving* (type 2), where a problem is framed in terms of causal relations between X and Y variables. Once the transfer function $Y = f(X)$ is determined, the problem is solved by determining optimal settings for the X variables that give the desired properties of the distribution of the Y variables ("response-surface optimization"). Many Six Sigma projects are also examples of *Science Research Problem Solving* (type 3 above). Emphasis in such projects is on the translation of the problem into one or a few measurable CTQ variables, which are then measured and analyzed. Based on techniques such as the control chart and the process capability analysis, the real problem is then established based on the collected data.

De Mast and Lokkerbol (2012) note that *People Problems* (type 4 above), which are the most complex, involving subjective perceptions, incongruent interpretations and conflicting goals, have traditionally not been on the radar in the quality engineering field.

Wicked Problems is another term, similar to complex problems, that was discussed in Rittel and Webber (1973) and later by Perry (2020). Some characteristics of wicked problems include the uniqueness of the problem, solutions that vary from good to bad from a stakeholder perspective, inability to learn by trial and error and difficulty in formulating the problem.

The difficulties of complex or wicked problems imply that it would be futile to try to provide a recipe or prescription for solving them, no matter what consultants may say. Rather, general principles and broader skillsets are needed. Adaptability and the ability to improvise depending on the nature of the complex problem become critical.

Figure 1 provides a framework to illustrate the dimensions of complexity we have most frequently experienced in projects. As we will discuss later, these can all be better understood through proper understanding of the problem context, shown in the center of Figure 1. The five dimensions surrounding problem context are problem definition, data access/structure/quality, analysis methods, decision making and solution deployment. The 6th dimension, organizational complexity, is the environment in which the five other dimensions exist. Organizational complexity is therefore critical to consider since every other type of complexity is impacted by the organization, including how technical resources are organized and how they do or do not work together.

These dimensions do not necessarily follow a linear pattern, but may function in parallel or at different times in a project. Our intent is not to try to categorize all the dimensions of complexity, but rather to highlight some potential areas to consider. Note that complex problems can be complex due to one, some or all of these dimensions. Outside of each dimension in Figure 1 we have provided some symptoms or examples of how that type of complexity appears in projects.

Potential role of the complexity framework in problem solving

Many authors (e.g., Robertson 2017) point to the work of the mathematician Polya (1957) as a landmark in the systematic analysis of problem solving as a discipline. Numerous authors on the topic cite his work. One of Polya's famous quotes is: "Trying to solve problems, you have to observe and to imitate what other people do when solving problems and, finally, you learn to do problems by doing them" (Polya 1957 p. 5). That is, learning how to solve problems requires that we study other people's thought processes, and imitate them.

Robertson (2017) looks at "how people solve problems" from a cognition and neuroscience point of view, that is, from how people think and how the brain functions. He lists four major cognitive steps in Polya's approach:

1. **Understand:** Understand the problem, to see what is required.
2. **Plan:** See how the items are connected, in order to make a plan to solve it.
3. **Do:** Carry out the plan.
4. **Check:** Look back at the solution, to review and discuss it. Reloop if necessary.

The similarities of Polya's steps to Deming's "Plan Do Check Act" process (Deming 1986) is hard to miss.

Robertson goes on to break each of these steps into two subcomponents, again based on cognition and neuroscience, resulting in eight individual steps:

- **Understand** - Identify problem, then define problem succinctly
- **Plan** - Analyze data, then form overall strategy
- **Do** - Organize information, then allocate resources
- **Check** - Monitor progress, then evaluate results

We focus here on addressing complex problems. There is, of course, also a significant body of literature on the topic of complexity. Fuller (1985) is a classic treatment of the issue of complexity in business processes, and how it can be systematically eliminated as a type of process improvement. George and Wilson (2004) build upon this foundation, noting how eliminating complexity can supplement other improvement initiatives, such as Lean Six Sigma. Complexity itself can be considered an academic discipline, typically focused on understanding the behavior of complex systems, such as in biology (Mitchell 2011). The current article does not attempt to review or develop the theory of complex systems, nor provide guidance on identifying and eliminating complexity from business processes.

Significant research has been conducted on each of the types of complexity noted in Figure 1. In our view, however, these research efforts have too often been conducted within individual academic "silos", without sufficient consideration as to how they fit together in solving real problems. For example, Weisbord (2012) provides significant detail on solution deployment and organizational complexity, and even discusses complexity in data collection, but says very little about complexity in analysis methods. Many, perhaps most, statistics textbooks cover the challenges of complexity in statistical analysis, but often "assume away" complexity in data quality by simply declaring that the data are a random sample from the population of interest.

The intended contribution of Figure 1 is therefore simply to integrate these different types of complexity into a single, high-level model. The proposed usage of this model is to facilitate more holistic thinking about complexity, and when addressing a specific problem, to proactively identify those types of complexity that are most likely to cause challenges, so that the problem-solving strategy might incorporate them. Below we explain each type of complexity at a fairly high level and provide references for more detailed study.

We illustrate use of this framework on a problem with order fulfillment that one of the authors (Roger) worked on. This also comes from Scott Paper Company, and involves the supply chain for consumer and commercial paper products, such as paper towels, toilet paper, and facial tissues. Some details have been altered to protect confidentiality, and elements of different individual projects have been combined for clarity. We explain the nature of the problem below when discussing complexity in problem definition.

Complexity in problem definition

Once a problem has been identified, it usually needs to be properly structured or rigorously defined. As noted by Russell Ackoff, one of the "founding fathers" of problem solving in operations research, what we typically see initially, unfortunately, is a "mess" (Ackoff and Vergara 1981). It is virtually impossible to solve a mess. Rather, we first need to convert the mess into a formal problem. Once we have a formal problem, we can move forward to solve it. The process of converting a mess into a problem is what we call problem definition or providing structure. This is often much more complex than one might think.

A well-structured problem is generally described as one for which the problem solver, although she does not know the solution, at least knows how to approach the problem. Routine problems fall in this category, for which the objectives and constraints are clear, and for which the problem solver can apply a known algorithm. For unstructured problems it is unclear how the problem should be approached, and typically, the objectives are unclear, or it is difficult to find a useful representation of the problem or an effective approach (e.g., Smith 1988; and Jonassen 2000). Especially if problems have multiple stakeholders, they tend to present themselves as a complex cluster of interrelated and interdependent issues, involving incongruent goals and subjective perceptions (Ho and Sculli 1997). Operations research and management science have produced many approaches for structuring such messes (e.g., Rosenhead 1996; Mingers and Rosenhead 2004; Shaw et al. 2004; and Eden 2004).

Consider the order fulfillment problem introduced previously. Scott management initially saw "a mess" in which there was too much finished product inventory (some paper products becoming damaged while stored in damp warehouses), too much work-in-progress inventory, also requiring storage and an "army" of forklift operators to move it around the factories, and upset customers who did not know where their promised product was or why it was late or incomplete. There were also manufacturing disruptions, dysfunctional teams that did not like each other and would not work across silos, recurring quality issues resulting in more work-in-progress and late shipments, and pressure from senior leadership demanding that the situation be "fixed" ASAP, but providing no methodology to fix it.

The problem could have been defined as a Checklist Problem (Pidd and Woolley's type 1 introduced above). In that case, the problem would have been framed as a standard inventory management problem, for which known, stepwise procedures are available in textbooks on industrial engineering and operations management (e.g., Hopp and Spearman 2008). The problem would have been defined as determining optimal safety-stock levels for the finished goods, deriving the required production quota and a suitable production schedule from there. Forcing the problem into such a template would remove all ambiguity and complexity. However, the drawback is that such standard formulas make restrictive assumptions, which may not be obvious to the users of the models. Also, they may oversimplify the problem, as here, and ignore relevant idiosyncrasies, or even solve the wrong problem altogether. The result is what is commonly referred to as an "error of the third kind;" obtaining the right solution to the wrong problem.

The problem could, alternatively and less simply, have been defined as a Definition Problem (Pidd and Woolley's type 2), and treated as a matter of finding the relevant cause-and-effect relationships, $Y = f(X)$. The problem solver might have tried to capture the goals in terms of Y variables such as the out-of-stock rate and inventory levels, and then tried to find the causal factors (X's) affecting them, such as production quota, replenishment levels and work in process (WIP) limits. Establishing the relationships between X's and Y's, they would have derived a solution strategy from there.

The problem could also have been defined as a Science Research Problem (Pidd and Woolley's type 3). In that case, the problem solver would have acknowledged that there are lots of opinions and perceptions, but no solidly established description of the current state of affairs or the desired end state. Instead, the problem solver would have investigated what the real problem seemed to be, and established the current state and desired end state based on data and facts.

Finally, and the most complex way, the problem could have been defined as a People Problem (Pidd and Woolley's type 4). Customers, manufacturing, sales and logistics all had their own perceptions of facts, issues and problems. Moreover, all of these stakeholders had partly incongruent goals, such as minimizing the stock-out rate (customers and sales), minimizing inventory levels to reduce carrying costs, storage costs and obsolescence (logistics), and maximizing the utilization of production facilities and workforce (manufacturing). Different perceptions and misaligned goals had created tensions and animosity, with various groups of people working against each other rather than collaborating. Defining the issue as a People Problem, the problem solver would have first tried to reconcile various viewpoints and perceptions, and negotiate with various factions to establish a shared goal.

The actual problem had elements of each of these types of problems, but no textbook solution. The organization had to define and scope the right problem, at the right level of complexity, considering the overall order fulfillment system. Since it is typically impossible to minimize inventory while at the same time maximizing productivity and minimizing late customer deliveries, what exactly would success look like? How would it be measured? This leads to the issue of organizational complexity, which we discuss shortly.

In this and many similar types of problems, there is no obvious problem statement or a single, quantitative objective to be maximized. Considerable work may be required to convert this mess into a formal problem that can be attacked, and to obtain organizational alignment across silos and with senior leadership that this is, in fact, the right problem. If organizational alignment is not obtained, then some members of the team may become "snipers" who actively look for ways to sabotage the team effort.

Frequent symptoms include confusion over the real problem being addressed, and developing a common set of objectives, without any "hidden agendas" being present. The scientific method, and objective prioritization tools can help here. Domain (subject matter) knowledge is particularly valuable with this type of complexity. Partnerships and collaboration with subject matter experts will be crucial here to ensure that the right problems are identified and tackled.

Complexity in data access, structure and quality

Textbooks typically present "pristine" data sets, each generally a "random sample" from the population of interest. There are no missing values or outliers, and the data presented are exactly the data needed to solve the problem at hand. Of course, the real world works quite differently! Experienced analysts know that random sampling is a model, an ideal that is rarely achieved in practice. Further, beyond worrying if the *data are right* (typos, missing values, outliers, and so on), we also have to worry about whether these are the *right data*. That is, do we have data on the right variables, collected the right way, from the right population, in the right time frame? Rarely, if ever, will the answer to this question be yes (Kenett and Redman 2019).

As an old saying goes, there is no "perfect" data set, despite textbook examples to the contrary. All real datasets have limitations, especially relative to the problem at hand. We argue that existing data should be viewed as "guilty until proven innocent", rather than the other way around. Further, as illustrated in the previous example in the Introduction, it may be impossible, or perhaps prohibitively expensive, to obtain the right data for a given problem.

Given that we will never have exactly the data we want, how should we handle the data we do obtain? Often the available data are from different sources, collected in different ways, with different limitations and biases. Many of these biases will not be known to the analyst, who is typically not the person who produced the data. This is why documentation of a data pedigree (Hoerl and Snee 2020) is so critical, but unfortunately also quite rare. Uncertainty about the quality of available data sets (right data and data are right), and also about how to integrate or combine the data in a logical manner, can result in considerable complexity. A general rule of thumb in applied statistics, especially when analyzing massive data sets (data science), suggests that roughly 90% of the overall analytics effort goes into obtaining, cleaning, verifying, integrating, and reformatting data, and only 10% into formal modeling and analysis. This complex work is rarely discussed at length in textbooks.

Incompatible data structures, such as some data sources being structured by customer, others by time, and others by product, are one common example. Proper documentation of the data pedigree, data modeling, and setting up proper data architectures in the first place, can provide useful tools. Note that data modeling is a term used in computer science and is *not* the same as statistical modeling. Data modeling is a well-developed field with different approaches for linking and integrating different sets of data in a way that enables more efficient analysis. Some reference materials on data modeling and how to address this type of complexity can be found in Simsion and Witt (2004), Hoberman (2009) and Kimball and Ross (2013).

When data were gathered to guide the team working on the Scott Paper order fulfillment system, issues became immediately apparent. First of all, it turned out that different paper mills used different formulas for productivity; even basic measures such as "up time" were calculated differently, for example in how they accounted for planned shutdowns. The inventory data turned out to be misleading, because upon closer inspection, some of the final and work-in-progress inventory had been damaged while in warehouses, reducing the actual product available. Further, customers frequently changed their requested delivery dates. Therefore, if a product delivery was late, it was not clear how to calculate how late it actually was.

Tools from computer science tend to be particularly useful in dealing with this type of complexity. There is a fast-growing field in addressing complexity of the data, with new jobs such as data architects, data modelers and data engineers becoming more prevalent. Individuals with experience in computer science and information technology tend to fill these roles and are increasingly important partners for those doing data analysis work.

Complexity in analysis

Problem analysis is often portrayed as consisting of two stages. Most of the focus in statistics is on model building, where relations between variables are described by a statistical model. Before the model-building stage, however, the problem solver must identify the relevant variables that are to be incorporated into the model. This variable-identification stage is often named exploratory data analysis (De Mast and Trip 2007). Complexity affects both stages in problem analysis.

Model building is the primary focus of much of the statistics profession. Journal articles cover increasingly complex types of analyses. The underlying models in statistical analysis can be more and more complex. Compare a simple linear model with standard assumptions such as independent, normally distributed errors, versus a more sophisticated generalized nonlinear mixed model that has both fixed and random effects, which might allow for different types of assumptions on the errors and be computationally challenging. The complexity may be due in part to the complexity of the structure of the data or due to the way the data were collected. For example, collecting sensor data in short-term intervals creates serial correlation that would need to be accounted for in the analysis. As another example, restrictions on randomization create split-plot structures in the data.

More complex models often require more complex analysis methods. For example, a hierarchical Bayesian model with multiple levels might require a more complex simulation mechanism to be able to obtain credible posterior intervals. A key issue in practice is that the assumptions of the more complex model may not be obvious to the analyst, who learns how to write code to conduct the analysis but may not understand the underlying theory. For example, more than once in our careers journal referees have insisted on random-effects models being applied when the factor levels were not chosen at random.

We should note that there are times when statisticians are guilty of proposing a more complex analysis when a simpler one would be adequate for the problem. This is often done without careful consideration of the assumptions underlying the more complex model. Our advice is that statistical models should never be more complex than can adequately be supported by the data. In our view, this is one of the underlying causes for the "reproducibility crisis" in science described in Baker (2016).

A solid understanding of statistical theory can help here. However, with the rise of "data science" as a unique, and at times competing discipline with statistics, fewer analysts performing complex analyses have solid backgrounds in statistical theory. Further, as academic statistics programs attempt to compete by adding more coding and computer science to their curricula, these theoretical foundations are not necessarily covered in depth. Tools from statistics/data science disciplines tend to be most useful in addressing this type of complexity.

Besides model building, where the relationships between X and Y variables are modeled, the identification of relevant X variables may also be hampered by complexity. Finding the causes, explanatory variables, or simply the X variables to be incorporated into the model may require some challenging detective work when it is not immediately obvious what the X's are, and instead, the problem solver must identify what characteristics or factors in a possibly complex system could be causing the problem she is trying to solve. If the space of potential problem causes is extensive, complex or ill-defined, it is easy to get overwhelmed by the sheer multitude of possibilities or to get bogged down in the wrong part of the search space. To deal with a complex search space, the literature proposes hierarchical strategies for identifying a problem's cause, which try to narrow down the search by a sequence of studies designed at eliminating whole classes of potential causes at once. Examples include Shainin's Eliminate-and-Zoom-in strategy Shainin (1993) and the Branch-and-Prune strategies discussed in De Mast (2011, 2013).

Analysis of the available Scott order fulfillment data was challenging due to the issues noted above, particularly the data quality issues. Of course, the complexity of problem definition also impacted analysis, because the specific objectives of analysis were not clear, or at least not agreed-upon by all parties. Understanding the limitations in the data, the initial analysis was quite basic.

Complexity in decision making

What is it that often makes decisions so hard to make? A textbook example of a problem would have a single criterion that needs to be optimized in some way. For example, it would be a simple decision to determine the best machine settings on manufacturing equipment to maximize the yield. However, the problem becomes more complex when more simultaneous criteria are added that must also be met. So it is not enough to just maximize the yield, but we are also trying to minimize the operating costs of the machine, minimize the time for changeovers between runs, and maintain an acceptable level of operator satisfaction by allowing them to take regular breaks throughout the day. If capital upgrades could further enhance yield, but require additional investment, this might or might not be warranted, depending on the financial state of the organization. There may not be a single "optimal" answer to a more complex decision that needs to be made.

Anderson-Cook (2017) provided some specific tools, such as Pareto fronts, to be able to address this complexity in decision making. If we can rigorously define the criteria that matter and collect the right data, then these tools can be quite valuable. Operations research (OR) provides another set of decision-making tools that can be helpful, such as discrete event simulation, queueing theory, and linear and quadratic programming. OR and Business Analytics discern several complexity classes of decision and optimization problems, such as *P*, *NP* and *NP-hard*. These classes characterize whether the problem's complexity allows an algorithm to solve it in polynomial time (P), or to verify a potential solution in polynomial time (NP, for nondeterministic polynomial time). NP-hard is the class of problems that are even more complex than NP (Arora and Barak 2009).

Complexity in the other elements often leads to complexity in decision making. For example, it may be very difficult to collect the right data. Other times, there are available data, but they have an uncertain pedigree, and are not the data needed to solve the problem. Of course, organizations have a human element. Perhaps intuition, politics, or emotions are getting in the way of a more rational approach to decision making.

We have also seen project teams get hung up on trying to collect vast amounts of "perfect" data to make the best possible decision. There is an opportunity cost that comes from delaying a decision, and it is important to recognize and quantify that cost. The term "paralysis by analysis" comes to mind. If you wait too long to decide whether to launch a new product, you may lose potential sales, assuming there are competitive options in the marketplace. Sometimes you have to employ the GEMO (Good Enough Move On) principle and recognize that moving forward now is the best option, despite some uncertainty.

As noted previously, while there were textbook solutions for inventory management, due to overly restrictive assumptions and the unique nature of the problem, these did not directly lead to consensus decisions as to how to optimize order fulfillment for Scott Paper.

Operations research, noted above, and general business management principles are particularly relevant disciplines here.

Complexity in solution deployment

A perfect solution, not implemented, is of zero benefit. The objective is not to simply find solutions and make decisions, but to fully deploy them in practice. This is much easier said than done, because many "solutions" are never implemented. The famous Netflix competition provides an excellent example. Netflix paid $1 million to the team that developed the "best" model to predict customer ratings of movies, provided it had at least a 10 percent improvement over the Netflix model in use at the time. A team won this competition, and the money, using an ensemble model involving 107 individual models. This "success" led to the creation of other modeling competition platforms, such as kaggle.com.

As noted by Donoho (2017), however, the winning solution was never actually implemented by Netflix, because they found that the time and expense involved in maintaining the 107 individual models were not worth the relatively minor improvement in accuracy. Further, the Netflix business model gradually migrated from mailing DVDs to online viewing. The data set used in the competition was no longer the most meaningful to Netflix' business. So, a team won the competition and the $1 million award, but the "solution" was never actually deployed, and therefore did not solve Netflix's business problem.

Because of all the previous forms of complexity, a selected solution may or may not be feasible to deploy. Further, even a very good solution can be botched in deployment, due to complexity in implementation. So how does one manage deployment complexity, when trying to benefit from a good solution? One option is the use of tools like a RACI matrix to identify the key individuals or groups responsible for different portions of a problem. The RACI matrix identifies who:

- Has overall *responsibility*
- Has direct *accountability*
- Needs to be *consulted*, and
- Needs to be *informed*.

This tool can also be used to identify key stakeholders who need to be a part of a solution to the problem. An example can be found in Lareau (2011). Change management efforts need to be considered to overcome different forms of resistance. Often, resistance to change is not intentional, it may simply be due to ignorance or lack of understanding of what the change means for the individual or group. While some resistance to change is natural, poor communication often results in entrenched resistance to change, and good solutions that are never actually deployed.

Deployment was a huge issue in the order fulfillment case. In addition to the sources of complexity noted previously, there was serious organizational mis-alignment, resulting in lack of consensus on tangible steps to address order fulfillment. In short, there was a tendency for each organization to want to optimize its own function, rather than the entire fulfillment system. For example, manufacturing was very reluctant to shut down, or even slow paper machines, despite there being minimal pull from the market for product at times. Eventual deployment of a solution was only achieved after addressing the organizational complexity issue.

Change management, rooted in psychology, is often needed even more than statistics or computer science here. There are several accessible business books on the topic such as that of Kotter (2012), but beware that recent and authoritative papers in the academic literature conclude that there is no consensus even regarding the nature of basic change processes (Stouten, Rousseau, and De Cremer 2018; Bamford and Daniel 2005).

Organizational complexity

The last element of complexity may be the most crucial to success. Organizational complexity refers to complexity in understanding the organization or environment in which the problem resides. We use a broad definition of organization ranging from companies, nonprofit groups or governmental entities. As soon as you have multiple people working together, you will have organizational complexity because of the diverse perspectives and experiences that they bring to the problem. We see organizational complexity as a type of People Problems discussed earlier, and in Pidd and Woolley (1980).

Some organizations are large conglomerates that span many physical locations around the world. Beyond many locations in different regions and countries, you may find that the supply chain spans many different suppliers, vendors, partners and customers. The complexity of a physical product (say a smartphone) can lead to a wide variety of groups both within and outside the organization involved in some portion of its development, manufacture, sales and distribution. Organizational design is one approach to organize individuals in a way to reduce complexity and give clear roles and responsibilities, including responsibilities for solutions to problems.

Teams that work across multiple time zones and regions are becoming more common as remote working environments are more prevalent. This creates challenges for teams to work together to tackle problems, and asynchronous efforts may be needed where everyone is not in the same room at the same time. Some examples of asynchronous efforts include crowdsourcing or idea generation platforms that tap into the power of the group to generate potential solutions to problems. These can allow many more individuals to participate in problem solving efforts.

Teams are also becoming more prevalent as the work gets more complex. For example, a more complex data project with larger amounts of data will require the efforts of more than one person. Davenport (2020) describes how teams with a mix of different skill sets are needed because the "data science unicorn," the superstar who can do it all, is rare, if not nonexistent. Since more data analysis work is being done by teams rather than individuals, organizational complexity will become even more critical than it has been previously.

Another approach to deal with organizational complexity is through the social networks of the individuals in the organization. Network analysis is a powerful tool to understand the way work really gets done, outside of the organizational charts and chains of command. Cross and Parker (2004) and Cross and Thomas (2009) provided a number of examples of

Table 1. Tools and disciplines addressing the dimensions complexity in problem solving.

Dimension	Symptoms (Examples) of Complexity	Tools and Methods	Discipline Focus
Problem Definition	Unclear problem statements, project scoping challenges, determining the right question to answer, unsure which problem to solve	Scientific Method, Exploratory Data Analysis, Costs/Benefits Analysis, Prioritization Tools, Problem Structuring	Domain Knowledge, Operations Research, Management Science
Data Access, Structure and Quality	Inconsistent data definitions, incompatible data systems, inordinate time preparing and cleaning data	Data Architecture, Data Modeling, Data Pedigree	Computer Science, Information Technology, Data Science
Analysis Methods	Incorrect or misleading analysis results, uncertainty in what method to use, software limitations for analysis	Statistical Theory and Models, Ad-hoc Analysis	Statistics, Data Science
Decision Making	Revisiting same decisions, going with intuition, disagreements on decision to take, delays in decision making	Operations Research, Pareto Fronts, Decision Engineering	Business Management, Operations Research
Solution Deployment	Not realizing full impact of process improvement, confusion on new ways of working, too many ways of working, no metrics to track progress	Change Strategy	Project Management, Change Management
Organizational Complexity	Ineffective teams, no clarity on roles and responsibilities, lack of vision or priorities, politics	Leadership, Team Management, Organizational Strategy	Business Management, Organizational Design

how a network view of an organization can allow for more innovation and improved performance. We believe this tool could be more widely used to understand the organizational complexity and then take action to address it as needed. For example, organizational network analysis could be used to identify people in the organization who are well-connected to many other areas in the organization. These people who serve as connectors would be important to consider in driving a change. They could be crucial to the success of a change as early adopters who help spread change more quickly in an organization.

The academic literature on the organization of quality improvement initiatives highlights various organizational factors that affect successful problem solving, such as an effective supportive infrastructure (Anand et al. 2009), fit with the organization's culture (Canato, Ravasi, and Phillips 2013), experience (Easton and Rosenzweig 2012), deployment guidelines (Lameijer, De Mast, and Does 2017), and various contextual factors (Swink and Jacobs 2012).

Organizational complexity turned out to be the greatest challenge in the order fulfillment case, and impacted all the other elements of complexity to some degree. The basic problem was that various constituencies (silos) within the organization had different, but unstated, objectives that related to optimizing their own silos. For example, the salesforce focused on making sales – by promising delivery times that manufacturing could not meet – and having product always available, without much regard for inventory. Manufacturing focused on having consistent production schedules to provide some sense of stability, and logistics was concerned about the carrying costs of excess inventory. These diverse objectives were due in part to the silos being "cross-incentivized," meaning that the VP of manufacturing was evaluated based on how much product was produced, but not on excess inventory levels. Similarly, the VP of sales was evaluated based on sales growth, not on unreasonable promises made to obtain those sales, and so on.

Further, the misalignment had existed for some time, and resulted in predictable personality conflicts between leaders, and subsequently their organizations. One individual in a manufacturing plant related: "There are two rules for working with corporate. The first rule is: never call corporate for help. The second rule is: if corporate offers help, decline." Cooperation across organizational silos was clearly not encouraged.

Leadership is key when addressing organizational complexity. Someone needs to recognize and work through the politics. This may be by edict, or by lower-level employees simply working together to get past negative politics. Organizational design and sound business management concepts tend to dominate technical methods in addressing such complexity.

Addressing complexity in problem solving

To summarize the preceding sections, Table 1 shows some of the tools and disciplines that are relevant for addressing differing elements.

Because there is a vast literature and multiple disciplines that address different areas, it should be clear that there are no "seven easy steps to addressing complexity". Further, books or consultants who suggest there are should be avoided. As we have seen, there are several dimensions of complexity, and in most complex problems there is more than one dimension. Organizational complexity, for example, is almost always present, if one is looking for it. Therefore, what follows should not be viewed as "seven easy steps," but rather some principles to guide teams as they struggle with complexity. The major principles include the following:

1. Identify and acknowledge complexity, not only in analysis, but in each of the areas noted in Figure 1.
2. Take time to understand the context of complex problems.
3. Take holistic approaches that combine data, analytics, subject-matter knowledge, organizational psychology, and so on.
4. Work toward deployment of sustainable solutions.

It may seem obvious, but identifying and acknowledging complexity is the first step. Just as it is impossible to help alcoholics who are in denial of their alcoholism, it is impossible to deal with complexity that is ignored or denied. For example, many business leaders will not readily admit, at least in public, that politics are at work in their organizations. But of course, they are.

We are not suggesting that problem-solving teams "overthink" simple problems, or waste time looking for complexity that is not there. If a machine is leaking oil, fix the leak. Do not take time to evaluate the organizational complexity. Therefore, the ability to utilize triage, and evaluate problems as being relatively straight forward, medium sized, or complex, is helpful. Problems differ in their complexity, and utilizing a complex strategy when a simple one will suffice is a poor use of resources.

One of the authors (Willis) recalls a conversation in which a Six Sigma project was being scoped. The Black Belt drafting the project charter was having a difficult time completing the different sections that were part of a document template. After a lengthy conversation, it was apparent that the solution was already well-known and understood and that it simply needed to be implemented. No exploration of root causes or problem-solving tools was needed. In this situation, the Black Belt was told that everything had to be a Six Sigma project and the solution was being forced into a methodology. It was not working very well. The adage is true "if you only have a hammer, everything looks like a nail". We should always use the right approaches (complex or simple) for the problem.

For complex problems, teams should carefully consider each of the potential dimensions of complexity in Table 1. Of course, this table does not provide an exhaustive list; these are simply the most commonly occurring dimensions of complexity in our experience.

2. Understand the context

One dimension of complexity that we have not discussed is understanding the context of the problem. This is because we feel that taking time to understand the context of complex problems can be part of the solution, not part of the problem. That is, by recognizing that complex problems are there for a reason (or reasons), and that previous attempts to solve them have failed for a reason (or reasons), we put ourselves in a much better position to properly diagnose, analyze, and eventually attack the problem. This approach is consistent with the saying: "For every complex problem, there is a simple solution. And it is wrong."

Consider the COVID-19 pandemic, which is the prevailing global medical challenge at the time of this writing. At first glance, the problem may be seen as purely epidemiological; for example, finding vaccines to prevent COVID. However, upon closer examination, there are other complexities in the context of this pandemic. For example, the specific ways in which COVID is transmitted are not yet fully understood. Treatment of COVID patients has improved considerably, but the best ways to treat those infected are still debated.

Looking at vaccine trials, the data from some of these trials have been seriously compromised (Lawton 2020). Poor understanding of data pedigree has led to poor models (Cropley 2020). Beyond data and modeling, there is a concern relative to maintaining a healthy economy during COVID. So, it is not clear if the real problem is simply to address COVID, or do so while keeping job loss and economic impact at "reasonable" levels. Who would decide what are reasonable levels? It is complex!

Further, there is a strong human element in combating COVID. Some people are willing to follow governmental guidelines, such as wearing masks and avoiding large gatherings, but many people are not willing to do so. Further, federal, state, and local

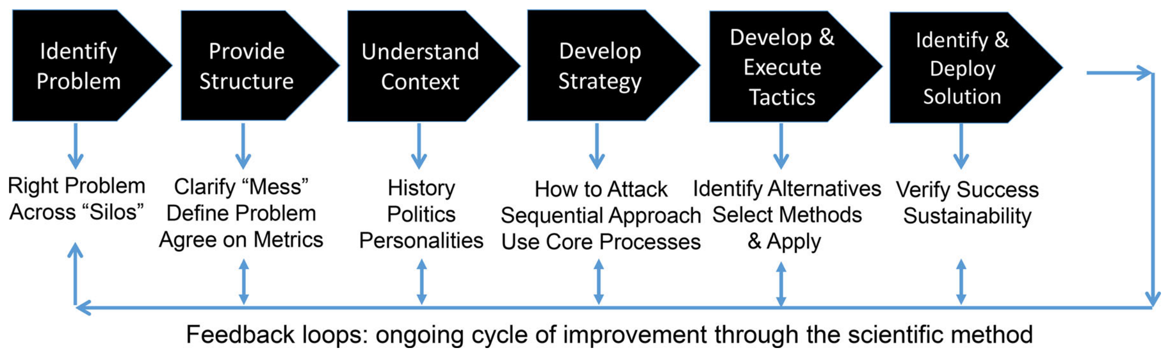

Figure 2. Phases of statistical engineering.

guidelines are not always consistent. The US Supreme Court has entered the fray, for example by overturning some executive actions, including restrictions on gatherings at houses of worship by Governor Cuomo of New York (Mckinley and Stack 2020). So COVID has an important legal context as well that must be understood.

Even if the current vaccines being rolled out ultimately prove safe and effective, that in itself will not "solve" COVID, because there are too many people who are unwilling to take vaccines in general, and COVID vaccines in particular ("anti-vaxxers"). So, the ultimate deployment of a "solution" will be quite a challenge. Finding a successful path forward will require a deep understanding of the full context of the COVID pandemic, which is quite different in different parts of the US, not to mention the world. Therefore, a holistic approach is needed, rather than focusing narrowly on developing vaccines.

3. Proper understanding of context leads to a more holistic approach

We argue that if the problem context is well-understood, this leads naturally to more holistic approaches, rather than purely technical approaches. In business, this leads to planning for all the complexities noted in Figure 1, in addition to the technical complexity. In the case of COVID, it would mean an integrated plan that takes into account the legal issues, the political issues, and the social issues, in addition to the technical epidemiological and public health problems.

How does one take a holistic approach? This is easier said than done. Typically, it requires development of an overall strategy, due to the complexity and the multi-faceted nature of the problem. Unfortunately, "strategy" is not a word typically found in the indices of statistics texts, or those of other technical disciplines. Some exceptions include Nelson (2018), as well as Hoerl and Snee (2020). Of course, Polya's model, mentioned previously, refers to "making a plan," while Robertson's extension of Polya's model specifically says to "form an overall strategy." So, the need to develop an overall strategy has been known for decades, but strategy is not often discussed in published case studies.

One organization that has thought deeply about developing overall strategies for solving complex problems is the International Statistical Engineering Association (ISEA, isea-change.org). This organization is focused on studying how to engineer solutions to large, complex, unstructured problems. The overall approach to attacking such problems is given in the Statistical Engineering Handbook, Chapter 1, which is available on the members-only section of the website given above (membership is free). This is reproduced below as Figure 2.

There are many problem-solving methodologies in the literature, perhaps the most well-known of which is the Define, Measure, Analyze, Improve, Control (DMAIC) process from Six Sigma. There are several uniquenesses of the statistical engineering approach shown in Figure 2 that are noteworthy:

- Formal statistical or other technical tools are not applied until the fifth phase. The first four phases involve getting a good handle on the problem, its context, and how it should be attacked.
- There is a full phase focused on nothing but understanding the problem context.
- There is a full phase focused on developing an overall strategy to attack the problem, based on an understanding of the full context of the problem.
- There are numerous feedback loops, illustrating that this is not typically a linear process in practice, but that problems often require movement back and forth between stages. Relooping is specifically mentioned in Polya's (1957) original work.

In the strategy phase, the team considers the full context of the problem, including all sources of complexity, and develops an overall approach, or strategy, for attacking the problem. This will typically require multiple tool sets, and often multiple disciplines. As noted previously, organizational psychology and subject matter knowledge will typically be heavily involved.

We argue that the approach shown in Figure 2 is not required for small problems, or even for most medium-sized problems. In our view, Six Sigma is an excellent approach to most of the medium-sized problems we have experienced in our careers. For large, complex, unstructured problems, however, a more holistic approach, with feedback loops, such as that shown in Figure 2, is needed. This is fully consistent with existing cognition and neuroscience, as explained by Robertson (2017).

4. Deploy sustainable solutions

As discussed previously, the Netflix competition is a prime example of a very complex technical solution that was never deployed. There are many others, such as the "epic failure" of the Google Flu Trend Model (Lazer and Kennedy 2015), which was deployed initially, but ultimately failed. This model, developed by Google, could predict outbreaks of the flu faster and more accurately than the Centers for Disease Control. Google Flu Trends was an early "poster child" for the power of big data. Unfortunately, as the users of Google evolved, and people's usage of Google changed over time, the model became more and more inaccurate, until Google "quietly euthanized the program."

Recently, Tom Davenport, who along with D.J. Patil wrote the original article in the Harvard Business Review (Davenport and Patil 2012) that popularized the term "data scientist," ran into the same issue. In his case, the specific concern was over roles and responsibilities for effective model deployment (Davenport, personal communication). He wrote in an article submitted for publication that data scientists should focus less of their effort on model building, and more effort on deployment of their models. A journal reviewer disagreed, arguing that the data scientist's job ends when the model is developed. Frustrated, Davenport appealed to the journal editor, who promptly agreed with the reviewer! Unfortunately, much of the data science community remains narrowly focused on model-building, viewing actual deployment of models or analyses to achieve sustainable results as outside their scope. The result is "… data scientists who are showing me the clever machine learning models they developed with more than 90% accuracy and complaining that the business people are ignoring their models and prefer to use their old manual process," discussed in the introduction.

The key point is that when the complexities noted previously are not taken into account, "solutions" that do not solve the real problem are often developed. They may be very good solutions for the stated problem, such as in the Netflix case, but not for the real business problem, with all its complexity. Therefore, deployment is not achieved by simply "pulling a switch," but through careful planning that takes all sources of complexity into account, including the human element. This generally requires a well-thought-out holistic strategy, as illustrated in Figure 2.

Success in the order fulfillment case was eventually achieved by applying these general principles at a new "greenfield" facility built by Scott. The new facility provided an opportunity to create new systems and structures to overcome the issues outlined above. For example, once complexity was acknowledged, a leader of the overall business process was named. This individual had responsibility for sales, manufacturing, and logistics for the product produced at the mill, helping to address the organization misalignment. Obviously, this individual saw the benefit of optimizing the overall business process, rather than individual "silos," and the organization carefully studied the overall order fulfillment system, developing a much better understanding of the context of the problem.

It therefore became much easier to obtain consensus on a succinct problem definition, which recognized the need not only for a technical, data-based solution, but also a solution that addressed the needs of the individuals and organizations involved. Of course, this was easier said than done, and required a lot of iteration between the different complexity elements, including acquisition of newer and better data, leading to more sophisticated analyses. Eventually, a good, although admittedly not optimal solution was agreed upon and successfully deployed across the organization, producing significantly enhanced results. This process was similar to a Lean Manufacturing approach, in that it was more of a "pull" than "push" system.

Conclusion and takeaways

We have described a framework for understanding different types of complexity as well as some principles to consider to address the complexity. There are no simple, prescriptive solutions for complex problems This complexity framework gives a broader view that encompasses statistical and other analysis approaches. As we have provided this framework and examples, we hope to encourage a more holistic approach to problem solving. However, a holistic approach may not be adequate without a recognition of the different types of complexity that impede various problem-solving approaches. For all the failures we have experienced because of not understanding the complexity, we have also seen successes because we took a more holistic view. From those successes, we are optimistic that complex problems can be effectively addressed.

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