Topics in Safety, Risk, Reliability and Quality

Patrick T. Hester
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Systemic Thinking

Fundamentals for Understanding Problems and Messes

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Contents

Part I A Frame of Reference for Systemic Thinking

1 Introduction 3
1.1 The TAO Approach 3
1.2 Systems Errors 3
1.2.1 Type III Error 5
1.2.2 Type IV Error 6
1.2.3 Type V Error 6
1.2.4 Type I and Type II Errors 7
1.2.5 Type VI Error 8
1.2.6 Type VII Error 9
1.2.7 Analysis of Errors 9
1.3 Observation 12
1.3.1 Theory-Laden Observation 14
1.3.2 Dynamic Model of Situated Cognition 15
1.3.3 Measurement 15
1.3.4 Bias and Heuristics 16
1.4 Summary 19
References 19

2 Problems and Messes 23
2.1 Introduction to Complex Problems 23
2.1.1 Historical Background for Complex Problems 24
2.1.2 The Machine Age and the Systems Age 25
2.2 Dealing with Systems Age Messes 26
2.2.1 Perspectives in Complex Problems 26
2.3 Holistic Understanding 28
2.4 Problem Formulation 29
2.5 Summary 32
References 33

3 Systemic Thinking . . . 35
3.1 A Brief Background of Systems Approaches . . . 35
3.2 What is Systemic Thinking? . . . 38
3.2.1 Age . . . 38
3.2.2 Unit of Analysis . . . 39
3.2.3 Stopping Criteria . . . 40
3.2.4 Goal . . . 41
3.2.5 Underlying Philosophy . . . 42
3.2.6 Epistemology . . . 43
3.2.7 Disciplinary Scope . . . 44
3.2.8 Approach . . . 44
3.3 A Methodology for Systemic Thinking . . . 45
3.4 Summary . . . 47
References . . . 48

4 Systems Theory . . . 51
4.1 Historical Roots of Systems Theory . . . 51
4.1.1 General Systems Theory . . . 51
4.1.2 Living Systems Theory . . . 52
4.1.3 Mathematical Systems Theory . . . 52
4.1.4 Cybernetics . . . 53
4.1.5 Social Systems Theory . . . 53
4.1.6 Philosophical Systems Theory . . . 53
4.1.7 Historical Roots of Systems Theory Summary . . . 54
4.2 Systems Theory . . . 54
4.3 Centrality Axiom . . . 57
4.3.1 Emergence . . . 57
4.3.2 Hierarchy . . . 57
4.3.3 Communication and Control . . . 58
4.4 The Contextual Axiom . . . 59
4.4.1 Holism . . . 59
4.4.2 Darkness . . . 59
4.4.3 Complementarity . . . 60
4.5 The Goal Axiom . . . 60
4.5.1 Equifinality and Multifinality . . . 60
4.5.2 Purposive Behavior . . . 61
4.5.3 Satisficing . . . 62
4.5.4 Viability . . . 62
4.5.5 Finite Causality . . . 63
4.6 The Operational Axiom . . . 63
4.6.1 Dynamic Equilibrium . . . 63
4.6.2 Relaxation Time . . . 63
4.6.3 Basins of Stability . . . 64

4.6.4 Self-Organization 65
4.6.5 Homeostasis and Homeorhesis 65
4.6.6 Suboptimization 66
4.6.7 Redundancy 67
4.7 The Viability Axiom 67
4.7.1 Requisite Variety 67
4.7.2 Requisite Hierarchy 68
4.7.3 Feedback 68
4.7.4 Circular Causality 68
4.7.5 Recursion 69
4.8 The Design Axiom 69
4.8.1 Requisite Parsimony 69
4.8.2 Requisite Saliency 70
4.8.3 Minimum Critical Specification 70
4.8.4 Pareto 71
4.9 The Information Axiom 71
4.9.1 Information Redundancy 71
4.9.2 Redundancy of Potential Command 71
4.9.3 Finagle's Laws on Information 72
4.10 Linkage of Systems Principles to Systemic Thinking Perspectives . . . 75
4.11 Summary 75
References 76

Part II A Methodology for Systemic Thinking

5 The *Who* of Systemic Thinking 81
5.1 Introduction 81
5.2 Brainstorm Stakeholders 82
5.3 Classify Stakeholders 84
5.4 Evaluate Stakeholder Attitudes 86
5.5 Determine Stakeholder Engagement Priority 89
5.6 Develop a Stakeholder Management Plan 95
5.7 Manage Stakeholders 96
5.8 Framework for Addressing *Who* in Messes and Problems 96
5.8.1 Example Stakeholder Brainstorming 96
5.8.2 Example Stakeholder Classification 97
5.8.3 Example Stakeholder Attitude Evaluation 97
5.8.4 Example Stakeholder Engagement Priority 98
5.8.5 Example Stakeholder Management Plan 100
5.9 Summary and Implications for Systemic Thinking 100
References 101

6 The *What* of Systemic Thinking 103
6.1 Decision Analysis 103
6.1.1 Group Decision-Making 106
6.2 Anatomy of a Problem 107
6.2.1 Outcome Selection 108
6.2.2 Output Characterization 109
6.2.3 Goal Selection 112
6.2.4 Derivation of Weights 113
6.3 Model Evaluation 115
6.3.1 The Pareto Principle 115
6.3.2 Optimality 115
6.4 Framework for Addressing *What* in Messes and Problems 117
6.4.1 Problem Identification 117
6.4.2 Outcome Derivation 118
6.4.3 Outcome Selection 118
6.4.4 Goal Specification 119
6.4.5 Weight Derivation 119
6.4.6 Problem Evaluation 119
6.5 Summary and Implications for Systemic Thinking 120
References 121

7 The *Why* of Systemic Thinking 125
7.1 *Why* as the Cause for Motivation 125
7.2 Motivation 126
7.3 Categorizing Theories of Motivation 126
7.4 Theories of Motivation 127
7.4.1 Instinct Theory of Motivation 127
7.4.2 Drive-Reduction Theory of Motivation 129
7.4.3 Hierarchy of Needs 130
7.4.4 Attribution Theory of Motivation 131
7.4.5 Reinforcement Theory of Motivation 131
7.4.6 Social Comparison Theory of Motivation 132
7.4.7 Path-Goal Theory of Motivation 132
7.4.8 Social Exchange Theory of Motivation 133
7.4.9 Theory X, Theory Y 134
7.4.10 Cognitive Dissonance Theory of Motivation 135
7.4.11 Equity Theory of Motivation 136
7.4.12 Social Learning Theory of Motivation 137
7.4.13 Expectancy Theory of Motivation 138
7.4.14 Motivator-Hygiene Theory of Motivation 140
7.4.15 Acquired Needs Theory of Motivation 140
7.4.16 ERG Theory of Motivation 141
7.4.17 Self-determination Theory of Motivation 141
7.4.18 Opponent Process Theory of Motivation 142

7.4.19 Goal Setting Theory of Motivation . . . 143
7.4.20 Reversal Theory of Motivation . . . 144
7.5 Applying Theories of Motivation . . . 145
7.6 Cybernetics and Control Theory . . . 145
7.7 Klein's Integrated Control Theory Model of Work Motivation . . . 146
7.8 Framework for Addressing *Why* in Messes and Problems . . . 147
7.9 Summary and Implications for Systemic Thinking . . . 149
References . . . 150

8 The *Where* of Systemic Thinking . . . 155
8.1 Context . . . 155
8.1.1 Perspectives and Context . . . 156
8.1.2 Description and Definitions for Context . . . 157
8.1.3 Elements of Context . . . 158
8.1.4 Temporal Aspects of Context . . . 160
8.1.5 Data, Information, Knowledge, and Context . . . 161
8.1.6 Extracting Procedural Context . . . 162
8.2 Boundaries and the Environment . . . 163
8.2.1 Definitions for Boundary and Environment . . . 164
8.2.2 The Significance of Boundary Establishment . . . 165
8.2.3 Boundary Classification . . . 166
8.3 Framework for Addressing *Where* in Messes and Problems . . . 166
8.4 Summary and Implications for Systemic Thinking . . . 169
References . . . 170

9 The *How* of Systemic Thinking . . . 173
9.1 Mechanisms . . . 173
9.1.1 Physical Classification for Mechanisms . . . 174
9.1.2 Human Classification for Mechanisms . . . 175
9.1.3 Abstract Classification of Mechanisms . . . 178
9.2 Methods as Mechanisms for Messes and Constituent Problems . . . 179
9.2.1 Sensemaking . . . 179
9.2.2 Pragmatic Intersection of Knowledge and Information . . . 180
9.2.3 Framework for Sensemaking . . . 181
9.3 Cynefin and Decision Analysis . . . 185
9.3.1 Decision Science . . . 186
9.3.2 Sub-disciplines of Decision Analysis . . . 186
9.3.3 Science-Based Decision Analysis Techniques . . . 187
9.3.4 Situation Awareness . . . 189
9.4 Framework for Addressing *How* in Messes and Problems . . . 191
9.5 Summary and Implications for Systemic Thinking . . . 193
References . . . 194

10 The *When* of Systemic Thinking 199
10.1 Life Cycles and Maturity 199
10.2 Evolution 205
10.3 Entropy 208
10.4 The Hierarchy of Complexity 211
10.5 Another View of Sensemaking 213
10.6 Framework for Addressing *When* in Messes and Problems 214
10.7 Summary and Implications for Systemic Thinking 216
References 217

11 Putting it All Together: A Systemic Perspective 219
11.1 Mess Articulation and Problem Selection 220
11.2 The *Who* Perspective 221
11.3 The *What* Perspective 223
11.4 The *Why* Perspective 224
11.5 The *Where* Perspective 226
11.6 The *When* Perspective 229
11.7 The *How* Perspective 230
11.8 Iteration 232
11.9 Summary 233
References 233

Appendix: Systemic Thinking Self-Assessment 235

Index 237

Part I
A Frame of Reference for Systemic Thinking

Chapter 1
Introduction

Abstract The first step to solving a problem is recognizing you have one. It is with this notion in mind that the authors begin their discussion. This chapter begins with the first tenet of systemic thinking which we term the TAO approach, a general approach for increasing our understanding about problems. Then, a discussion of systems errors is presented. In order to mitigate these errors, we discuss the importance of observation as it pertains to making conclusions about our problems. Issues associated with observation and the effects of bias are then discussed.

1.1 The TAO Approach

As we said before, we've all got problems. Some are big, some are small. Some are fleeting, while some are nagging and persistent. All could benefit from a structured way of reasoning about them. To that end, we provide an initial perspective for reasoning that we deem the TAO approach, for **T**hink, **A**ct, and **O**bserve. The relationship between these elements is pictured in Fig. 1.1. While there are many approaches to undertaking each of these steps, this book concentrates in large part on discussing the systemic thinking approach, a method for undertaking the *Think* step.

Knowing that we have problems and more importantly, knowing that we need approaches to deal with these problems, requires us to first understand what systematic mistakes we make that may be avoided. To this end, we turn to a discussion of systems errors.

1.2 Systems Errors

As we discussed in the preface, most difficult problems can be characterized by (1) intransparency, (2) polytely, (3) complexity, (4) variable connectivity, (5) dynamic developments, (6) time-delayed effects, (7) significant uncertainty, and

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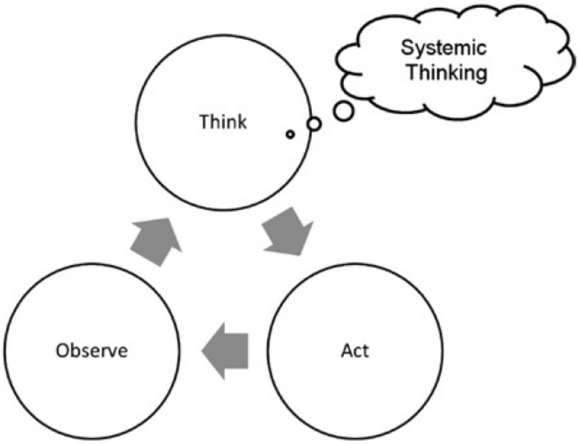

Fig. 1.1 TAO approach to reasoning

Table 1.1 Science sector and field of science that have conducted inquiry on errors (adapted from [3])

Science sector	Field of science	Reference
Social sciences	Educational sciences	Betz and Gabriel [6], Kaufman et al. [23], Marascuilo and Levin [32, 33], Onwuegbuzie and Daniel [44], Rosnow and Rosenthal [46, 47]
	Psychology	Games [13], Kaiser [22], Leventhal and Huynh [28], Levin and Marascuilo [29, 30], Meyer [34], Mitroff [36], Mitroff and Featheringham [37]
	Economics and business	Boal and Meckler [7], Umesh et al. [54]
Natural sciences	Mathematics	Kimball [24, 38,40–42], Tracz et al. [50]

(8) humans-in-the-loop. Each of these has a substantial element of human perception and interpretation. The way in which a problem is thought about, acted on, and observed is a major determinant of the degree of uncertainty, competition, and unpredictability associated with the problem context. Reasoning about a complex problem routinely employs the use of one of a number of systems-based approaches [18–20]. Analytical and interpretational errors are common while thinking about, acting on, and observing problems; however, none of these systems approaches explicitly addresses these potential errors. Further, despite their prominence, there is not an agreed-upon taxonomy for errors in problem solving approaches. Thus, the authors have worked to establish an initial taxonomy for error classification [2, 3]. This taxonomy has drawn from research performed by researchers representing four of the 42 fields of science [43], as depicted in Table 1.1.

Based on our review of the literature in Table 1.1, we were able to develop a taxonomy of seven common errors that individuals are prone to encounter while thinking about, acting on, and observing problems. For reasons that will become clear once this discussion is complete, we will not discuss the errors in numerical order; rather, we begin with discussion of the Type III error.

1.2.1 Type III Error

The extant literature on the Type III (γ) error originated in statistics. Frederick Mosteller [1916–2006], one of the most eminent statisticians of the 20th century, reported:

> In other words it is possible for the null hypothesis to be false. It is also possible to reject the null hypothesis because some sample O_i has too many observations which are greater than all observations in the other samples. But the population from which some other sample say O_j is drawn is in fact the right-most population. In this case we have committed an error of the third kind. (p. 61)

This is commonly referred to as "the error associated with solving the wrong problem precisely" [36, p. 15].

Type III errors normally occur during the formulation of problems, the phase in which the actual details surrounding the reported problem are exposed, validated and verified as part of the process of problem reformulation (reformulation is where the initial *reported* problem statement is validated by relevant stakeholders). We denote this revised problem statement the *formulated* problem, to differentiate it from the reported problem. Failure to reformulate the reported problem is the most common source for a Type III error.

Adams and Hester [2] devise a medical analogy to explain the Type III error:

> The systems practitioner faced with a reported problem needs to act much like a physician. The physician listens to the symptoms reported by a patient, but does not accept the diagnosis of the patient. The physician cannot rely solely on the patient's story and symptoms, but must gather empirical data by conducting tests, taking physiological measurements, and conducting a physical examination. The systems practitioner is in a similar professional relationship with the client that has a systems problem. Problem reformulation ensures that the scope of the problem is properly abstracted from the real-world and defined. The problem system must be adequately bounded, include empirical data of both the quantitative and qualitative types, and include an understanding of both the environment and relevant stakeholders. (p. 28)

Mitroff and Featheringham [37] elaborate on the importance of proper problem formulation.

> The initial representation or conceptualization of a problem is so crucial to its subsequent treatment that one is tempted to say that the most important as well as most difficult issue underlying the subject of problem solving is precisely 'the problem of how to represent problems.' (p. 383)

Failure to properly define the scope of the problem results in inadequate problem statements and is commonly referred to as "the error committed by giving the right answer to the wrong problem" [22]. Once we have appropriately formulated our problem (i.e., thought about it), we must decide what to do about this problem (i.e., act on it). In acting (or abstaining from action), we may encounter a number of errors, to which we now turn.

1.2.2 Type IV Error

A review of the extant literature on Type IV (δ) errors shows that this type of error has been discussed principally in the psychology and the educational sciences. To the authors' knowledge, the first mention of the Type IV error in the literature was by Marascuilo and Levin [32]. They define the Type IV (δ) error as:

> A Type IV error is said to occur whenever a correct statistical test has been performed, but is then followed by analyses and explanations that are not related to the statistical test used to decide whether the hypothesis should or should not have been rejected [33].

The primary discussion related to Type IV errors has been associated with statistical testing, most notably ANOVA models [23, 46, 47, 54]. We prefer, however, to endorse the Type IV error as one concerned with a higher level of abstraction, most notably as "the incorrect interpretation of a correctly rejected hypothesis" ([32], p. 398).

Boal and Meckler [7] elaborate on the problems caused by a Type IV error, introducing the concept of solutions as iatrongenic:

> Acting to solve a problem, be it the right problem or the wrong problem, can create other difficulties. Sometimes solutions are 'iatrogenic,' meaning that they create more, or bigger problems than they solve. Faced with such a possibility the decision maker should thoroughly examine all the potential system effects, and perhaps refrain from action. In the case that it was an attempted solution to the right initial problem, one important problem is now replaced by another, perhaps worse problem. (p. 333)

Thus, even though the problem has been correctly identified (i.e., thought about), the action identified to resolve the problem is incorrect. Further, there is potential in this situation for the identified actions to actually exacerbate the problem.

Adams and Hester [3] continue their medical analogy:

> This type of error also has a medical analogy. This could be the case where the physician commits a Type IV (δ) error by correctly diagnosing the problem and prescribes the right medication. However, the medication side-effects for a particular patient are worse than the original symptoms. The systems practitioner is prone to committing this error. The most typical instance is when the practitioner has properly reformulated and defined the client's problem and then applies an improper solution approach (i.e., methodology, method, or technique) in an attempt to resolve this problem. Failure to match the solution method to appropriate solution of a problem has been an important subject in the systems literature [4, 17, 21]. (pp. 320–321)

1.2.3 Type V Error

The Type V error, like the Type IV error, concerns actions taken in support of problem resolution. The field of cybernetics and the systems *principles of homeostasis* [8] and *homeorhesis* [55] inform individuals that systems have the ability to self-regulate to maintain a stable condition. Thus, some problems may solve themselves by simply allowing a natural order to restore itself. The converse of this is that many problems require intervention in order to be addressed and simply wishing for a problem to disappear on its own will not make it go away. There is a substantial risk in not acting when action is called for. Boal and Meckler [7] discuss this sentiment as the Type V (ε) error:

> Deciding to take no action, when no action is called for, is the correct solution. However, falsely believing that the problem will either solve itself or simply go away is an error of the 5th kind. Such errors allow the situation to linger, at best, or to fester and worsen requiring greater resources to solve. (p. 334)

In the medical analogy of this error, the physician commits a Type V error when he or she correctly diagnoses an ailment (i.e., thinks about the problem properly), yet fails to take corrective action to resolve the problem. The reason for the failure to act in this case may reside in the physician's belief that the ailment will simply resolve itself.

Causes for the Type V error are many. Lack of stakeholder consensus (e.g., the doctor, insurance company, and patient do not agree on treatment options) may lead to inaction due to the lack of a singular prevailing option, or due to a predominant stakeholder forcing an inaction strategy (e.g., the insurance company denies a request for an MRI, leading to a wait-and-see approach). Further, there may be a fundamental lack of understanding which permeates the analysis of the problem. This may lead to the stakeholders being unable to generate a plausible scenario for resolving the problem. Finally, stakeholders may fear worsening the problem by interfering. While this is a valid concern, we must weigh the balance between the Type IV and Type V errors, that is, between taking the wrong action and taking no action. Once we have acted, we must now observe the effects of our actions. In observation, there are also opportunities for committing errors.

1.2.4 Type I and Type II Errors

The extant literature on the Type I and Type II errors is founded in the mathematics (i.e., statistics) field of science, originating with Neyman and Pearson [40–42]. The Type I and Type II errors have been explored extensively in the literature associated with these fields. They are driven by discussions of statistical inference; specifically, they are motivated by the traditional two-sided hypothesis test. In such a test, there are only two possible error conditions: (1) deciding that a difference exists when, in fact, there is none (i.e., committing a Type I (α) error), and (2) deciding there is no difference when, in fact, there is a difference (i.e., committing a Type II (β) error) [22]. Table 1.2 contains a representation of and definitions for the Type I and Type II errors framed in terms of the testing of a null hypothesis, H_0.

To continue our medical analogy, there are two classic examples from the medical world of the Type I (α) and Type II (β) error, based on the premise of H_0 being the hypothesis that a person does not have a disease:

- *Type I (α) error*: A medical test indicates a person has a disease that they do not actually have.
- *Type II (β) error*: A medical test indicates a person does not have a disease that they do actually have.

Table 1.2 Type I and type II errors

	Actual condition	
Test result	H_0 true	H_0 false
Reject H_0	*Type I Error* (α) False positive	Correct action True positive
Fail to reject H_0	Correct decision True negative	*Type II Error* (β) False negative

Both of these errors typically occur after the problem has been thought about and acted on (and after practitioners hopefully have avoided committing a Type III, IV, or V error). Thus, this phase is considered to be the observation phase (observation, as we intend it, will be elaborated on later in this chapter). Another potential error of observation is the Type VI error.

1.2.5 Type VI Error

Here we introduce a Type VI (θ) error as one that is well known yet not characterized in error terms traditionally. This error is that of unsubstantiated inference. Succinctly, Holland [16] states famously, "Correlation does not imply causation…" (p. 945). Given two variables, *A* and *B*, we can measure the strength of the relationship between these variables, known as their correlation. If we continue our medical analogy, denoting *A* as the number of tests taken to diagnose an illness and *B* as money spent on treatment, then we see what is termed a positive correlation between these two variables, meaning that the more tests that are performed, the more money that is spent. We can now change *B* to money remaining in your bank account. As additional tests are ran, assuming they are being paid for by you, your bank account balance decreases, indicating a negative correlation. The correlation coefficient measures the strength of the relationship between these two variables.

Causation is not as straightforward, however, and it is often erroneously taken as a given when correlation is present. For example, if we have two additional events, (1) a man receives a positive test for a given disease (*A*) and (2) his brother receives a positive test for the same disease (*B*), we may be able to establish correlation. However, inferring that *A* caused *B* or *B* caused *A* is faulty, unless we have information (more specifically, observations) that corroborates this assumption, e.g., the disease in question is a blood-borne disease and the brothers admit to sharing needles during drug use. In this case, we might be able to establish causality. More often than not, however, our notion of causality is simply conjecture. This behavior represents the Type VI error. In fact, there are four possible outcomes for any two correlated variables, *A* and *B*:

1. *A* could cause *B*.
2. *B* could cause *A*.

3. An additional third variable, C, could be contributing to the change in both A and B.
4. It may simply be a coincidence that the two events have a correlation.

We must be careful not to infer causality regarding A and B in an effort to explain unknown phenomena. Establishing causality requires significant observation and should not be done erroneously.

1.2.6 Type VII Error

A Type VII (ζ) error occurs when errors of Types I–VI compound to create a larger, more complex problem than originally encountered. Boal and Meckler [7] elaborate on the nature of Type VII errors:

> …the resulting problem may no longer be recognizable in its original form. The problems are not easily diagnosable, the resources and choices available become less sufficient or desirable, the solution is not readily apparent, and the solution not so attainable. (p. 336)

Complex systems problems that are open to multiple errors may be referred to as messes [1] and are in sharp contrast to those denoted as *tame* by Boal and Meckler [7]. It is the Type VII error that we must truly be concerned about. Complex problems are further exacerbated by committing a Type VII error, a "system of errors" ([2], p. 30) to complement Ackoff's characterization of messes as "systems of problems" ([1], p. 100).

Adams and Hester [2] complete their medical analogy by discussing this error:

> …a Type [VII] error can be conceived as one that first involves a physician diagnosing an incorrect problem for a patient, perhaps due to incorrect information provided by the patient (thus committing a Type III error). Let's suppose for the sake of argument that the patient is uninterested in receiving a true diagnosis of his symptoms as he fears grave news from the physician, so he downplays his symptoms. Given this incorrect (and under-emphasized) problem, the physician decides to take no action to a problem otherwise requiring action (thereby committing a Type V error). His reasoning, based on the information he's received, is that the problem will go away on its own. The problem, untreated, worsens, thereby resulting in an inoperable condition, such as the progression of a benign cancer to a stage at which treatment is unavailable. Clearly, this system of errors has exacerbated the original in a form unimaginable by the original stakeholders (i.e., the patient and physician). (p. 30)

1.2.7 Analysis of Errors

We have discussed seven classifications of errors that may be experienced while thinking about, acting on, or observing a problem. A taxonomy of the seven systems errors is presented in Table 1.3.

Recalling the TAO approach, we can see when individuals may be prone to these errors. *Thinking* is prone to the Type III error, *acting* to the Type IV or V

Table 1.3 Taxonomy of systems errors (adapted from [2])

Error	Definition	Issue
Type I (α)	Rejecting the null-hypothesis when the null-hypothesis is true	False positive
Type II (β)	Failing to reject the null-hypothesis when the null-hypothesis is false	False negative
Type III (γ)	Solving the wrong problem precisely	Wrong problem
Type IV (δ)	Inappropriate action is taken to resolve a problem as the result of a correct analysis	Wrong action
Type V (ε)	Failure to act when the results of analysis indicate action is required	Inaction
Type VI (θ)	Inferring causation when only correlation exists	Unsubstantiated inference
Type VII (ζ)	An error that results from a combination of the other six error types, often resulting in a more complex problem than initially encountered	System of errors

error, and *observation* to the Type I, II, or VI errors. In order to correctly address a problem, all of these errors must be avoided as follows:

1. The Type III error must be overcome; that is, the correct problem must be formulated. This is, in large measure, the focus of this book. *Thinking systemically* about a situation allows us to ensure we have formulated the correct problem for action and observation.
2. Once we have thought systemically about our problem, we must now act (or not). This offers the opportunity for three possible outcomes:
   a) We act incorrectly, when action is warranted (committing a Type IV error).
   b) We fail to act, when action is warranted (committing a Type V error).
   c) We act correctly, when action is warranted (committing no error).
   Thus, we must choose the appropriate course of action for a particular problem, given that choosing not to act is also a feasible choice. This can only be achieved if we first think systemically about our problem, ensuring our ensuing actions appropriately address the problem we are dealing with.
3. Finally, we must observe the effects of our actions (or lack thereof). This must include consideration of avoiding the Type I and Type II errors by conducting appropriate statistical analyses and making appropriate conclusions based on these analyses. Further, we must avoid the Type VI error by ensuring our conclusions are supported by evidence and not by conjecture. More on this observation process is presented in the next section.

To illustrate the potential interaction of these errors with the TAO approach, Table 1.4 illustrates the TAO approach applied to reasoning about a disease.

The timeline in Table 1.4 can continue, ad infinitum. That is, you may continue to think, act, and observe with respect to your headache problem. This series of steps is shown graphically in Fig. 1.2 in a manner adapted from Boal and Meckler [7] and (Adams and Hester [2, 3]), but focused on the probabilities associated with

Table 1.4 Example TAO timeline and potential errors

TAO stage	Situation description	Potential error(s)
Think	Recurring headaches cause you to try to figure out their source. Lacking an obvious environmental trigger, you decide to make an appointment to see your primary care provider	Type III
Act	You make an appointment with your doctor based on your thinking	Types IV, V
Observe	Your doctor observes you, asks you questions, and collects information	Types I, II, VI
Think	Based on the information provided and their own perspectives, the doctor reasons about your condition	Type III
Act	The doctor, with your consent, agrees to schedule you for an MRI	Types IV, V
Observe	Your insurance company collects the request from your doctor, and considers it in concert with your medical history. Given your lack of prior concerns and lack of current evidence, the insurance company denies your claim	Types I, II, VI
Think	Given the reduced options available, your doctor thinks about your situation. Your doctor suggests you go home and start an activity log to keep track of your food, sleep, and activity habits to identify any underlying patterns	Type III
Act	You maintain your activity log for two weeks	Types IV, V
Observe	You return to the doctor and the doctor observes your activity log, making recommendations based on the results (to include a second attempt at securing insurance approval for an MRI)	Types I, II, VI
And so on…	You can continue to think, act, and observe. Even though the problem may seem resolved (i.e., your headaches go away), there is likely to be an implicit recognition of the danger of their recurrence. Thus, you may devote brain power to the awareness of their presence, no matter how distant they are in memory. The problem, as you see it may evolve from "How can I make these headaches go away?" to "How can I ensure these headaches do not return?"	Types I–VII

particular paths available to an individual. It is worth noting that Type VII errors are represented by the different error combinations presented in Fig. 1.2 (i.e., a Type III error followed by a Type I error). Note that P(α), P(β), P(γ), P(δ), P(ε), P(θ), and P(ζ) represent the probability of a Type I-VII error, respectively.

Note that the shaded boxes represent the only scenario in which no errors are committed. It is easy to see, qualitatively, how prone we are to errors based purely on the number of opportunities for us to commit one (or more) errors. Combining these error probabilities together, we can devise an equation for the calculation of the probability of a correctly addressed problem. This can be computed as shown in (Eq. 1.1).

$$P(\mathit{correctly\,addressed\,problem}) = 1 - [[1 - P(\gamma)][1 - (P(\delta) + P(\varepsilon))] \\ [1 - (P(\alpha) + P(\beta) + P(\theta))]] \tag{1.1}$$

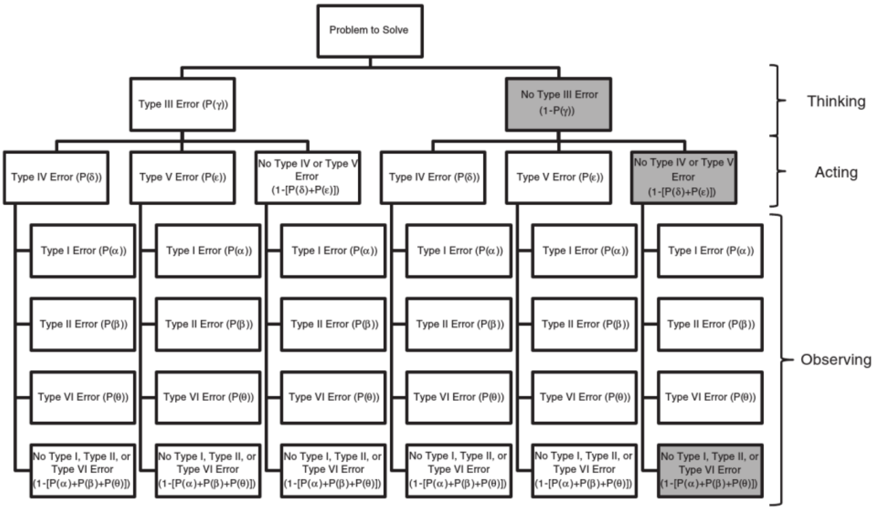

Fig. 1.2 Tree depiction of systems errors

Correctly addressing a problem requires that we think about, act on, and observe the situation appropriately, thus, we do not commit any Type I-VI (and, by definition, Type VII) errors. While we can calculate $P(\alpha)$ and P(β) in a very straightforward manner, the remaining quantities are more difficult, if not impossible, to discern. It is more important to understand that errors are serial; thus, our approach to understanding is only as strong as its weakest link, be it in our thinking, acting, or observation. Committing any error drastically reduces the likelihood that we correctly addressed our problem. Thus, we must be diligent in addressing each of these errors.

1.3 Observation

Here we elaborate on the notion of observation as it pertains to the TAO process and to systemic thinking in general. Observation is the central source of knowledge gained from exposure to the real world. This is true whether the knowledge is being generated in a controlled laboratory or in a natural setting.

> Observation is being understood in a very broad way here, to include all kinds of sensory contact with the world, all kinds of perception [14, p. 156].

Observation is the operation where raw sensory inputs are filtered by the human thought process. The physiological capacity for sensory perception in humans is limited by the five senses: (1) hearing, (2) sight, (3) smell, (4) taste, and (5) touch. Over time, raw perceptions are converted by the human thought process and begin

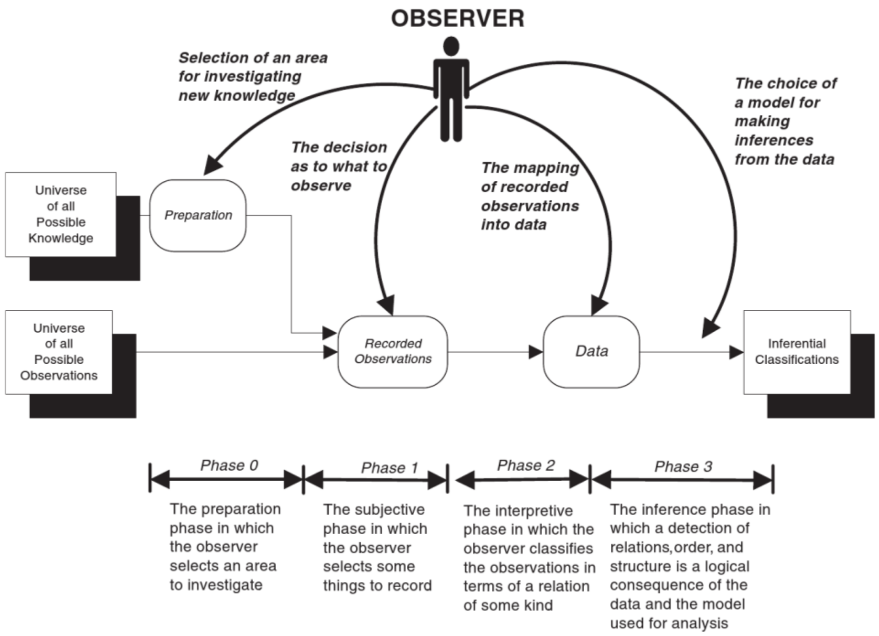

Fig. 1.3 Flow diagram of observable to inference

to form impressions, which are stored for future use. Stored impressions and their relationships with one another are formed into constructs that permit the individual to develop more complex implications and associations from the sensory inputs.

In a literature too vast to summarize here, theorists have argued that observation is already cognition and that we cannot describe a fact without implying more than the fact. As a result, Clyde H. Coombs [1912–1988] proposed that the term *data* be used for observations already interpreted in some way. The diagram in Fig. 1.3 depicts the scope of Coombs' [9] theory of data.

Figure 1.3 depicts how an observer's interpretation of the universe of all possible observations can lead to logical inferences as a result of four distinct phases conducted during the process of observation. The graphic has additional importance when considered with the following statement from Coombs [9] pertaining to those phases after Phase 0:

> The scientist enters each of these three phases in a creative way in the sense that alternatives are open to him and his decisions will determine in a significant way the results that will be obtained from the analysis. Each successive phase puts more limiting boundaries on what the results might be. At the beginning, before phase 1, there are perhaps, no limits on the potential conclusions; but each phase then constrains the universe of possible inferences that can be ultimately drawn from the analysis. (p. 5)

It is important to note that the observer depicted in Fig. 1.3 directly influences the data in many ways. Table 1.5 provides a glimpse of the how the observer influences the observations during the four phases and associated stages.

Table 1.5 How and where an observer exhibits influence during observation

Phase	Stage	Description
0—preparatory	Knowledge area	Selection of an area for investigating new knowledge
	Preparation	Preparatory reading in the area's existing body of knowledge
1—subjective	Selection	Selection of things to observe
	Method	The sensors and methods used to record and measure the observation
2—interpretive	Analysis	The observer interprets the data
	Classification	The observer classifies the observations
3—inferential	Inference	The observer makes an inference based on the order structure and model used in analysis and classification
	Publication	The observer reports the interpretation of the new knowledge

Table 1.5 demonstrates that the potential to influence observations is problematic and must be mitigated during the conduct of all research and problem solving efforts. Thus, in terms of the stages of observation and their relation to our systems errors, we must be careful to avoid the Type I and II errors in Phase 2 and the Type VI error in Phase 3.

This leads the discussion to the notion that all observation is impacted by the observer's personal beliefs in what is termed *theory-laden observation.*

1.3.1 Theory-Laden Observation

Based upon the notion that observation has already been subjected to analysis, a number of major scholars in the field of Philosophy of Science have argued that observation is theory-laden [12, 26]. Specifically,

> Observation cannot function as an unbiased way of testing theories (or larger units like paradigms) because observational judgments are affected by the theoretical beliefs of the observer [14, p. 156].

Paul K. Feyerabend [1924–1994] [12] cautions all observers of empirical data to separate the observation from the consequent description:

> We must carefully distinguish between the 'causes' of the production of a certain observational sentence, or the features of the process of production, on the one side, and the 'meaning' of the sentence produced in this manner on the other. More especially, a sentient being must distinguish between the fact that he possesses certain sensation, or disposition to verbal behavior, and the interpretation of the sentence being uttered in the presence of this sensation, or terminating this verbal behavior. (p. 94)

Many theories and models exist for further reading into awareness, observation, and cognition. While this subject area is beyond the scope of this text, the reader is referred to literature on situation awareness [11], the recognition-primed decision (RPD) model [25], and gestalt psychology [10] for further guidance on the topic. We turn to the Dynamic Model of Situated Cognition as one model for observation.

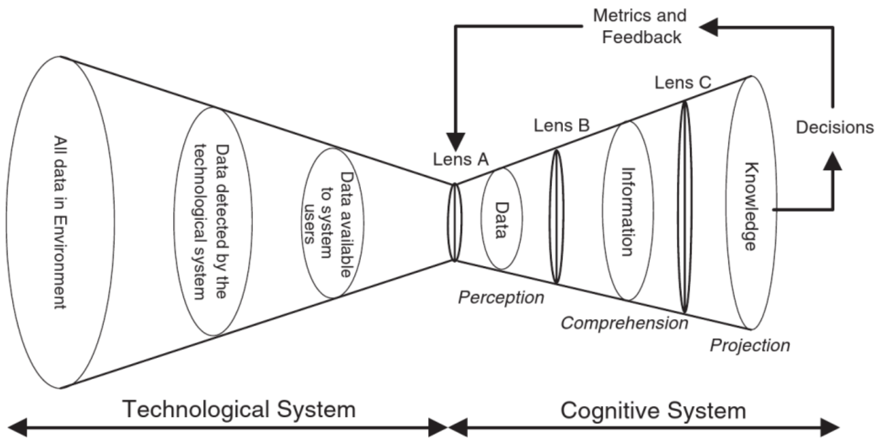

Fig. 1.4 The dynamic model of situation cognition

1.3.2 Dynamic Model of Situated Cognition

The theory-laden observation process must involve consideration of both technological and human elements and can be thought of as residing within a larger construct. A model to describe this observation process is the Dynamic Model of Situated Cognition (DMSC), which captures both the human and technological components of systems in a single model that depicts how observation is influenced by a variety of agents [35, 49]. Figure 1.4 is our depiction of the DMSC, that aligns the terminology of Miller and Shattuck to be consistent with Coombs and ours'; specifically, Coombs' central thesis was that *data* are recorded observations that have already been subjected to analysis.

The final output of the DMSC is used to make decisions, which are then measured with metrics and then used as feedback to the system. The key insight from Fig. 1.4 is a graphical representation of the observation to decision process. In translating observations to usable data, we intentionally (and unintentionally, based on our own perceptions and technological limitations) remove observations from consideration, as all observation is theory-laden and influenced by our human biases.

1.3.3 Measurement

Good science is based upon four generally accepted criteria that ensure quality: (1) truth value, (2) applicability, (3) consistency, and (4) neutrality [31]. The third criterion addresses the consistency in the generation of knowledge and establishes guidelines for ensuring consistency and stability during generation (i.e., design and technique), of new knowledge. The ability to accurately repeat observations, independent of the original observer, is an essential element. The requirement for independent reproducibility ensures that observations by different observers are comparable. Because the physiological capacity for input perception in humans is subjective and qualitative (i.e., the five senses react differently from human to human) this makes them difficult to record and hence, compare.

The concept for measurement evolved to permit different human observers to record and compare observations made at different times and places. Measurement consists of using observation to compare the real-world phenomena being measured to an established standard which can be reliably reproduced for use by multiple, independent observers. Measurement's goal is to reduce an observation to a discrete measure which can be recorded and used as the basis for comparison with other measures.

Quality criterion such as reproducibility may be invoked through the use of formal methods and measurement. However, the nagging issue and difficulties generated by the presence of theory-laden observation must be addressed by an understanding of how bias is introduced into the process. This leads the discussion to the mitigation of bias as an element of personal beliefs during observation.

1.3.4 Bias and Heuristics

Our ability to observe is affected, both negatively and positively, by our own biases and heuristics. First, we discuss bias, defined as:

> Any process at any stage of inference which tends to produce results or conclusions that differ systematically from the truth [48, p. 60].

Bias may be introduced during each and every stage and phase depicted in Fig. 1.3. As a result, the observer must ensure that the process depicted in Fig. 1.3 provides reasonable controls that mitigate bias.

> The difficulties generated for scientific inquiry by unconscious bias and tacit value orientations are rarely overcome by devout resolutions to eliminate bias. They are usually overcome, often only gradually, through self-corrective mechanisms of science as a social enterprise [39, p. 489].

Part of understanding how to mitigate human bias requires knowledge of the source and major types of unconscious bias. Because all human beings have unintentional cognitive biases that affect their decision making, knowledge of the types of bias may help improve their detection and elimination. Cognitive biases include behaviors that are labeled *heuristics*. Table 1.6 lists a variety of definitions for the term heuristic.

The unintentional biases and heuristics that operate at the subconscious level are the most difficult to prevent. The sections that follow will provide a short discussion of major heuristics and how to mitigate their effect.

Table 1.6 Definitions for heuristic

Definition	Source
A heuristic is a procedure for achieving a result which does not consist simply in applying certain general rules which are guaranteed to lead to the result in question	[45, p. 165]
A rule or solution adopted to reduce the complexity of computational tasks, thereby reducing demands on resources such as time, memory, and attention	[5, p. 379]
Heuristics are 'rules of thumb' that are used to find solutions to problems quickly	[27, p. 242]

1.3.4.1 Availability Heuristic

The availability heuristic refers to the practice of basing probabilistic evidence on an available piece of information from one's own set of experiences [51, 52]. That is to say, humans estimate the likelihood of an event based on a similar event that they can remember, which is by definition, from a biased and unrepresentative sample in their memory. Further, since newer events provide greater saliency in one's mind, they influence an individual's reasoning to a larger degree than do older events. Additionally, events with unusual characteristics stand out in one's mind (i.e., you don't remember the hundreds of times you went to a given restaurant, but you definitely remember the time you got food poisoning). Furthermore, humans may be biased based on the retrieval mechanism that is utilized to obtain the experience from their memory. Depending on who is asking the question, for example, an individual may consciously or unconsciously block memories. In order to mitigate this problem, observers should include mechanisms that account for how their experiences bias the data they retrieve about a particular set of observations.

1.3.4.2 Representativeness Heuristic

The representativeness heuristic refers to the phenomena when individuals assume commonalities between objects and estimate probabilities accordingly [52]. The determination of similarity between objects is typically performed by comparing their known attributes. Individuals compute a running tally of matches versus mismatches and then estimate whether or not the item fits a category based on the total. Once the item is categorized, automatic category-based judgments are made about the member item. Using this type of analysis has its issues. To combat this bias, individuals must use base rates (i.e., unconditional, or prior, probabilities) to compare the underlying category probability versus the specific scenario. Then, the base rate can be adjusted to accurately reflect the specific scenario's characteristics (i.e., its conditional factors).

It should be noted that availability and representativeness are often confused, but they are not the same phenomenon. With availability, individual instances are retrieved and a judgment concerning the frequency of the item is made based on the item's saliency and ease of information retrieval. Alternatively, representativeness involves retrieving information about generic concepts and then a similarity match is made between the item in question and a proposed category. The category association, along with goodness-of-match or degree of similarity, produces confidence or a frequency estimate.

1.3.4.3 Conjunction Fallacy

Another bias that individuals may be prone to is the conjunction fallacy [53]. Tversky and Kahneman [53] introduce this phenomenon with the following example: Linda is 31, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice and also participated in antinuclear demonstrations. Is she more likely to be (a) a bank teller, or (b) a bank teller and active in the feminist movement?

The overwhelming majority of survey respondents answered *b*, despite the fact that *b* is more restrictive (and therefore less probable) than *a*. People report the more complicated scenario as being *more real* or that it *made more sense*. The conjunction fallacy is counteracted by analyzing individual event probabilities and then combining them.

1.3.4.4 Anchoring and Adjustment Heuristic

Another bias is the anchoring and adjustment heuristic [51]. Humans establish anchors as starting points for their judgments and base subsequent observations on the initial value that was provided to them. In other words, early values will be given higher weights than subsequent values and as such will serve as *anchors* for future analysis. Anchors tend to bias future information that is sought and included in one's analysis. The status quo is a powerful anchor. It is often easier for individuals to take an existing value and adjust it to their specifications. The anchoring and adjustment effect can be either beneficial or detrimental and may be combated by independently generating values prior to the observation of values in the real-world.

1.3.4.5 Recognition Heuristic

The recognition heuristic refers to the heuristic by which an individual selects an alternative that is the most familiar to them [15]. While it seems to be a fundamentally unsound approach to decision making, Goldstein and Gigerenzer [15] discovered experimentally that this approach often outperforms more rigorous approaches to decision making. It can be useful for *on the fly* decision making in inconsequential scenarios such as deciding on a restaurant while on a road trip based on restaurants you recognize (e.g., McDonald's or Subway) or buying a pair of shoes based on brands that you've worn in the past and know to be reliable (e.g., Nike or Adidas). However, this approach has both positive and negative effects and should be avoided in conducting empirical observations.

1.4 Summary

Complex problems demand approaches that can account for their inherent complexity, rather than ignore it and hope it goes away. That is the underlying premise of this book. To that end, this chapter introduced the TAO approach to thinking systemically about a problem. We then discussed a taxonomy for errors that we are prone to when seeking increasing understanding. We continued with a discussion of observation and its importance in mitigating errors. Finally, we discussed biases and heuristics and their effect on observation.

After reading this chapter, the reader should:

1. Understand the TAO approach;
2. Have an appreciation for errors and how to avoid them; and
3. Understand how to conduct bias-free observation.

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Chapter 2
Problems and Messes

Abstract As problems have evolved from simple systems to complex systems, so too must the methods we use to address them. However, machine age problems, consisting of simple systems, have traditionally been viewed from a largely technical perspective. In systems age complex problems, a predominantly technical perspective continues to be used at the expense of other complementary perspectives. Complex problems have been viewed, and hence, addressed, with a single predominant lens which has often been unsuccessful in solving many ill-structured, wicked, or messy problems. The development of multiple perspectives requires those faced with solving complex problems to include additional perspectives in order to achieve understanding. This includes the integration of hard and soft perspectives to ensure that, in addition to the technical perspective, the equally important organizational, political and human perspectives have been included. The application of multiple perspectives offers a more inclusive framework through which complex problems may be viewed. The integration of technical, organizational, political and human perspectives widens the aperture through which a problem is analyzed, which then increases the probability of correctly addressing ill-structured, wicked, and messy problems. Embracing these complementary perspectives, guidance is given on how to begin to decompose our mess into a number of discrete problems for analysis.

2.1 Introduction to Complex Problems

This section will give a brief historical background for the emergence of the systems age and how problems in the systems age are differentiated from those in the machine age.

P. T. Hester and K. M. Adams, *Systemic Thinking*, Topics in Safety, Risk, Reliability and Quality 26, DOI: 10.1007/978-3-319-07629-4_2,

2.1.1 Historical Background for Complex Problems[1]

The genesis for most approaches for handling ill-structured, wicked, or messy problems has been attributed to the increase in the complexity of these problems. Early pioneers in the systems field[2] emphasized increasing system complexity as the principal driver for new approaches, although they recognized that this was far from a complete explanation [10, 11]. To explain this, some historical background is warranted.

Problem solvers have been approaching complex problems using a predominantly technical perspective since the advent of large-scale systems in the fledgling radio, television, and telephone industries in the United States during the 1930s. This was a result of the recognized need for an approach to deal with problems encountered during the development of modern telecommunications services. The Radio Corporation of America (RCA) and its subsidiary, the National Broadcasting Company (NBC), were interested in the expansion of their television broadcast domain. At the same time, the Bell Telephone Company was interested in the expansion of their long-distance telephone network. Both companies initiated technical studies aimed at increasing their markets through the use of new broadband technologies that were beginning to emerge in the early 1940s. Most of the exploratory studies and experimentation in the commercial sector were interrupted by the Second World War.

During the Second World War, the American military used large numbers of scientists and engineers to help solve complex logistical and strategic bombing problems related to the war effort. Many of these efforts made significant contributions to the philosophy and techniques of what was then called Operations Research. At the same time, the need for many novel types of electronic gear for airborne use gave rise to a wide variety of component devices, popularly known as *black boxes*. "These were ingenious devices, but their application in terms of the entire system of which they were merely parts was a matter of improvisation" [10]. Inevitably, many of the engineers and scientists working on these *black boxes* were required, by necessity, to look ahead to the ultimate goal—the system. When the war ended, a number of corporations (most notably the RAND Corporation, the Bell Telephone Laboratories, and RCA) hired much of this pool of talented scientists and engineers to provide services to both the government and the telecommunications industry. These seasoned practitioners were able to capitalize upon the lessons from their war-time experiences in the development and implementation of the modern telecommunications and electrical power systems. The telecommunications system development efforts provided an impetus for much of the early literature on systems approaches [11, 12].

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[1] Much of this information comes from a conference paper by Adams and Mun [5].

[2] The early systems field included operations research, systems analysis, and systems engineering.

Table 2.1 Ackoff's machine age and systems age characteristics

	Machine age	Systems age
Description	Simple system	Complex system
Boundary	Closed	Open
Elements	Passive parts	Purposeful parts
Observable	Fully	Partially
Method of understanding	Analysis and reductionism	Synthesis and holism

2.1.2 The Machine Age and the Systems Age

Russell Ackoff [1919–2004, 1] used the terms *machine age* and *systems age* to refer to eras that were concerned with two different types of systems problems. The machine age was concerned with simple systems, and the systems age is concerned with complex systems. Table 2.1 contrasts the most basic characteristics of the machine and systems ages.

Ackoff [2] recognized that the technical perspective of the machine age was inadequate for coping with what he termed the *messy* situations present in the systems age, where human activity systems were predominant. Ackoff coined the concept of a *mess* and *messes* in 1979 when he used the idea in two papers where he was arguing that operational research was passé and that a more holistic treatment of systems problems was required [2, 3]. He foresaw that a wide variety of disciplines would be necessary to solve systems problems. Ackoff's [2] definition of a mess and messes is worthy of review:

> Because messes are systems of problems, the sum of the optimal solutions to each component problem taken separately is not an optimal solution to the mess. The behavior of the mess depends more on how the solutions to its parts interact than on how they interact independently of each other. But the unit in OR is a problem, not a mess. Managers do not solve problems, they manage messes. (p. 100)

The bottom line is that complex problems in the real-world must include a definition of human activity in the development of the contextual framework for the problem. For Ackoff [2], context was the essential element that modern systems age problem solvers would need to include in each problem formulation if complex systems were to be understood and later resolved. He argued that the utility of operations research had been diminished because most of the established machine age techniques were unable to account for the complexity caused by humans that were present in almost all systems age problems. Burrell & Morgan [8] support Ackoff's contention, stating:

> Mechanical models of social systems, therefore, tend to be characterized by a number of theoretical considerations and are thus of very limited value as methods of analysis in situations where the environment of the subject is of any real significance. (p. 61)

In short, the methods and techniques of traditional operations research are "... mathematically sophisticated but contextually naïve and value free" [14]. Ackoff's work established the need for a clear understanding of specific or relevant context as fundamental to understanding and analyzing systems age problems.

Additional support for Ackoff's notions was provided by Nobel laureate Herb Simon [1916–2001] who addressed what he labeled the *ill-structured problem*. Simon [23] states that "an ill-structured problem is usually defined as a problem whose structure lacks definition in some respect" (p. 181). A systems age problem is ill-structured when circumstances and conditions surrounding the problem are potentially in dispute, not readily accessible, or lack sufficient consensus for initial problem formulation and bounding. There may be multiple and possibly divergent perspectives or worldviews, rapidly shifting and emergent conditions that render stable solution methods innocuous, and difficulty in framing the problem domain such that the path forward can be engaged with sufficient alignment of perspectives to remain viable. Rittel and Webber [20] termed this a *wicked problem*, where:

> The information needed to understand the problem depends upon one's idea for solving it. That is to say: in order to describe a wicked-problem in sufficient detail, one has to develop an exhaustive inventory of all conceivable solutions ahead of time. The reason is that every question asking for additional information depends upon the understanding of the problem—and its resolution—at that time. Problem understanding and problem resolution are concomitant to each other. Therefore, in order to anticipate all questions (in order to anticipate all information required for resolution ahead of time), knowledge of all conceivable solutions is required. (p. 161)

The immediate result of a wicked problem is the questionable ability of traditional approaches based upon a single technical perspective to be successful.

2.2 Dealing with Systems Age Messes

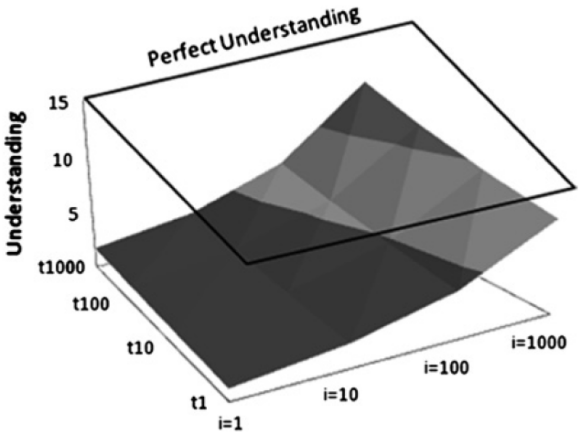
Most systems age messes include those factors we identified in the preface, namely (1) intransparency, (2) polytely, (3) complexity, (4) variable connectivity, (5) dynamic developments, (6) time-delayed effects, (7) significant uncertainty, and (8) humans-in-the-loop. From our point of view, it seems reasonable to assume that the way in which a systems age mess is perceived by its solution participants is a major determinant of the degree of these factors that each of the solution participants is able to clearly identify as part of the problem analysis.

2.2.1 Perspectives in Complex Problems

Because there is not a single true reality or correct perspective of any systems age problem, the systems *principle of complementarity* [7] must be applied. The principle simply states:

> Two different perspectives or models about a system will reveal truths regarding the system that are neither entirely independent nor entirely compatible.

Fig. 2.1 Depiction of increased understanding as a function of Time (t) and Perspectives (i)



If we think of a perspective as the state of one's ideas or the known facts, then we can represent the world-view of the observer as a function of the number (i) of perspectives (P_i) utilized to represent the problem under study. Equation 2.1 [4] is a mathematical representation of contextual understanding for a limited number of perspectives (n).

$$Contextual\ Understanding = \sum_{i=1}^{n} P_i \tag{2.1}$$

Perfect understanding requires complete knowledge of the infinite number of perspectives, a fact that problem solvers struggle to control when bounding messy, ill-structured, or wicked problems. Equation 2.2 [4] is a mathematical representation of perfect understanding.

$$Perfect\ Understanding = \sum_{i=1}^{\infty} P_i \tag{2.2}$$

A depiction of these concepts is shown in Fig. 2.1. This figure shows that as both time (t) and the number of perspectives increases, our understanding increases dramatically. Perfect understanding (i) is depicted as a plane that we attempt to attain but cannot reach no matter how much time passes or how many perspectives we consider.

Because, by definition, our scope of perspectives is limited, we can never have perfect understanding, and thus, we must strive to increase the value of our contextual understanding.

The universe of acceptable decisions available to you to move from your current state to desired state is your *problem space*. This problem space may include several intermediate steps which each move the current state incrementally closer to your desired end state. Identification of the delta between our current and desired states is a useful and practical means for us to articulate our problem. Readers interested in more on means-ends analysis, problem solving computer algorithms, and early developments in artificial intelligence are referred to Newell and Simon [19].

Even knowing these basic characteristics doesn't make problem formulation any easier. It is not a straightforward endeavor, for many of the reasons we've talked about so far, e.g., any time we have multiple divergent perspectives, the complexity of our situation increases substantially. Vennix [24] agrees, stating of messy problems:

> One of the most pervasive characteristics of messy problems is that people hold entirely different views on (a) whether there is a problem, and if they agree there is, and (b) what the problem is. In that sense messy problems are quite intangible and as a result various authors have suggested that there are no objective problems, only situations defined as problems by people. (p. 13)

As such, problem identification is not trivial. Further, the question of problem identification can have different levels of importance depending on the situation that we are facing—discerning that our stomach pains are really appendicitis likely is more important than choosing what we will have for dinner, and yet both situations may be perceived to meet Sage's four criteria. Indeed, problems are omnipresent and, often times, overwhelming.

To assist individuals in dealing with their problems (or more appropriately, their messes), we suggest modern approaches to reductionist problem solving are insufficient, not because they suggest we decompose a problem, but because, after analysis of this singular problem, they often ignore the reintegration of this problem into the context of which it is a part. Just like no man is an island, no problem exists in isolation. Our appendicitis problem must also consider insurance, transportation to the doctor, family history, alcohol and drug use, and diet, while our dinner choice must consider our finances, social obligations, fellow diners, availability of cuisine, and time constraints.

After problem-centered analysis, all conclusions concerning problem understanding must be considered as part of a coherent whole in order to holistically reason about our mess, as shown in Fig. 2.3. Thus, we suggest, during the thinking stage of the TAO approach, first articulate a mess as best as possible by identifying problems associated with it (there are five shown in Fig. 2.3, with two being grayed out, suggesting either they weren't identified or purposefully chosen to be ignored for the purposes of the analysis). Each of the selected problems (P_1–P_3 in the case of Fig. 2.3) is then analyzing using the methods detailed in Chaps. 5–10. These perspectives are then reintegrated as detailed in Chap. 11, in order to provide for understanding at the mess level. This increased understanding acts as an input to the act and observe stages of the TAO approach.

Thus, within the thinking step of the TAO approach, we begin by asking the most fundamental initial question, namely, *What problems are we trying to solve*?

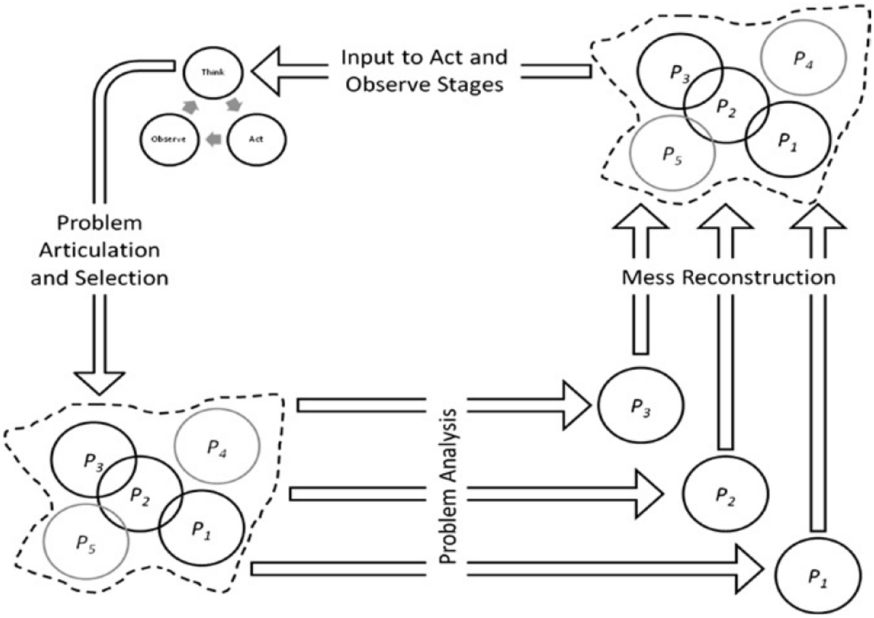


Fig. 2.3 Illustration of mess decomposition and reconstruction

Each mess will contain *many* problems, and we must think systemically about each in order to reason about our mess.

Hammond et al. (2002) discuss the importance of problem formulation: "The way you state your problem frames your decision. It determines the alternatives you consider and the way you evaluate them. Posing the right problem drives everything else" (p. 15). Formulation of your problem must include an appreciation for characteristics of the systems they are associated with. Churchman and Ackoff [9] noted a number of similarities in purpose-built objects (i.e., man-made systems). Three of these similarities are important to our study of messes and to the formulation of our problem:

1. Presence of Choice: "The basis of the concept of purpose is the awareness of voluntary activity" ([21], p. 19). Choice is essential to identify purpose.
2. Inclusion of Time: "Purposive behavior can only be studied relative to a period of time" [9, p. 35].
3. Production Requirement: "The purposive object or behavior is at least a potential producer of some end-result (end, objective, goal)" [9, p. 35].

Purposive behavior, a characteristic of all man-made systems, requires a system to have choices (alternatives) and to produce some desired behavior over a period of time. In order to identify and formulate our problem (or accompanying mess), one must appreciate the underlying purpose of its associated system. Ignorance of purpose will no doubt result in inappropriate analysis and a propensity for committing a Type III error [15–17]. It is in our best interest to ensure that this problem truly reflects the concerns of relevant stakeholders in order to avoid this error. This is sometimes easier said than done as we don't always have complete latitude over this exercise, however. In fact, our problem may be predefined by some authority (such as a customer) or the organization in which we work. Hammond et al. [13] agree, urging decision makers to consider the trigger, the initiating force, behind their problems. They caution, "Most triggers come from others…or from circumstances beyond your control…Because they're imposed on you from the outside, you may not like the resulting decision problems" (pp. 18–19). In this case, at a minimum, we should work with other stakeholders to refine the problem in a manner conducive to gaining further understanding. If we can influence our problem formulation, we need to consider what triggered the problem so that we can ensure we've identified the root problem.

In all, problem formulation is neither trivial nor to be taken lightly. "Defining the problem is sometimes the most difficult part of the process, particularly if one is in a rush to 'get going'" [6, p. 48]; recall our notion of humans having a bias for action. Hammond et al. [13] warn of the pitfalls in taking problem formulation lightly:

> Too often, people give short shrift to problem definition…In their impatience to get on with things, they plunge into the other elements of decision making without correctly formulating the problem first. Though they may feel like they're making progress in solving their problem, to us they seem like travelers barreling along a highway, satisfied to be going 60 miles an hour—without realizing they're going the wrong way. (p. 26)

One final point on problem formulation. We should be careful to specify a problem that is unique enough to be relevant to our concerns, yet not so specific that it predefines a solution. This is important because a true problem may have predispositions towards a solution, but if we already have a solution, then we don't have a problem (i.e., we've got nothing to solve and we've violated the problem criteria suggested by Sage [22]). Only once we've formulated our problems and are satisfied they are representative of the concerns we wish to explore, can we begin to change our way of thinking about the problems in question. At this point, we are ready to think systemically.

2.5 Summary

Complex problems continue to be viewed from a largely technical perspective. Adopting a single technical perspective has been unsuccessful in solving many ill-structured, wicked, or messy systems problems. The application of multiple perspectives offers a more inclusive framework through which complex problems may be viewed.

The integration of technical, organizational, political and human perspectives during the analysis of the problem widens the aperture and provides an increased