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THE THREE WORLDS OF TASK COMPLEXITY

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ABSTRACT

Aim/Purpose	To provide a systematic approach to defining task complexity using a three worlds model previously introduced in informing science research.
Background	The task complexity construct presents researchers with a quandary. While it appears useful on the surface, repeated attempts to define it rigorously have failed to gain traction in the broader research community. The level of inconsistency between definitions is shown to have changed little in the past 20 years.
Methodology	Using a common framework that treats task complexity as a latent construct residing between sources and outcomes, moderated by both task familiarity and task discretion, separate models for each of the three worlds are developed.
Contribution	Our paper proposes a potential path forward by showing how many issues in past task complexity research can be reconciled by framing the construct according to the three worlds model: the world we experience, the world of human artifacts, and the "real world."
Findings	The framework defines experienced complexity as occurring in the mind of the task performer while performing a single task instance, intrinsic complexity as a function of the internal characteristics of the problem space used to perform a bounded set of task instances, and extrinsic complexity as the ruggedness of the fitness landscape in which the task is performed.
Recommendations for Practitioners	It presents a hypothetical example of how the model might be applied to the task of determining author contributions to a paper.
Recommendations for Researchers	It offers a path to convergence for definitions of task complexity.

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Future Research	The three worlds of task complexity can potentially be applied to many practical problems.
Keywords	task complexity, rugged landscape, objective complexity, familiarity, discretion

INTRODUCTION

Who cares about "task complexity?" Intuitively, the answer would seem to be everybody. We live in a world where the term "complexity" is widely and frequently used. Assertions such as "the complexity of our work lives is growing" would likely provoke little argument – even if we are not precisely sure what they mean. Why wouldn't we want to apply the concept to the tasks we perform in life and in our jobs?

Viewed from a research perspective, however, the use of task complexity raises many red flags. Over the past four decades, several attempts have been made to define the task complexity construct. Despite these efforts, researchers applying the construct have not come to a consensus on what the construct represents (Hærem et al., 2015). Worse, different approaches to the construct often lead to contradictions, threatening the internal validity of the research.

The study of task complexity has a long history in informing science transdiscipline. In the seminal paper that laid out the case for informing science, Cohen (1999) states:

> The driving force behind the creation of informing environments and delivery systems is that a task needs to be accomplished (p. 217).

Six years later, T. G. Gill and Hicks (2006) did a systematic review of the task complexity literature, confirming earlier noted inconsistencies in task complexity definitions and proposing five classes of definition. Subsequently, these five classes were abstracted into three dimensions (T. G. Gill & Murphy, 2011). The three dimensions, in turn, were identified as closely paralleling the three worlds (Schmitt & Gill, 2019), as described by Popper (1972). The objective of the present paper is to provide a greater level of rigor in advancing the three task complexity constructs, to demonstrate how they can be conceptualized using a more general framework, and to consider how they might apply to informing science research and to practice.

We begin by examining how perspectives on task complexity have evolved over the past decade. We conclude that they continue to differ across researchers and have exhibited little convergence since they were first examined in the informing science literature (i.e., T. G. Gill & Hicks, 2006). We then review how task complexity can be conceived through the lens of Popper's (1972) three worlds: (a) the world experienced within our minds, (b) the world as humans represent it symbolically (i.e., the problem space), and (c) the "real world" as it interacts with the task. Using the terminology adopted in the informing science literature (e.g., T. R. Gill & Gill, 2024), we refer to these three worlds of task complexity as *experienced*, *intrinsic*, and *extrinsic,* respectively. We then introduce a common model across the three worlds in which each form of task complexity is treated as a latent construct between sources of complexity and outcomes of complexity, moderated by the constructs of familiarity and task discretion.

In our subsequent discussion, we consider how the worlds interact with each other. We then examine the potential implications of the framework for both informing science research and practice. Finally, we offer some comments on the limitations of the research and possible future directions.

A BRIEF HISTORY OF TASK COMPLEXITY

Before presenting the three-world framework for characterizing task complexity, we must first justify why yet another attempt to define the task complexity construct is warranted. Hærem et al. (2015)

and Liu and Li (2012) already offer excellent reviews of the evolution of the construct. In this section, we highlight key contributions in that evolution with the objective of assessing whether the construct is approaching convergence.

The best-known systematic attempts to clarify the meaning of the task complexity construct appeared in the 1980s. The first of these, Wood (1986) emphasized that a task's complexity was inseparable from how we defined a task. He proposed four general ways a task could be characterized: (i) as a stimulus provided to the task performer ("task qua task"); (ii) as a set of behavior requirements; (iii) as a set of behavior descriptions; and (iv) as a set of ability requirements. Drawing most heavily on the first and second of these, he characterized a task in terms of acts, products, and information cues. Using this conceptualization, he proposed three sources of complexity: (1) *component:* a function of the number of distinct acts required to perform the task; (2) *coordinative:* describing the relationship between task inputs and products; and (3) *dynamic:* capturing the degree to which changes over time in the task environment impact the relationships between inputs and products as the task is performed. Total complexity was then defined to be a function of three sources. In Wood's perspective, a task's complexity could be determined based on the characteristics of the task itself, largely independent of the performer.

The second contribution, Campbell (1988), reviewed existing research that employed the task complexity construct. Campbell argued that the way task complexity was defined or used fell into three general categories: (1) psychological experience, defined in terms of what the performer experienced; (2) task-person interaction, defined in terms of the characteristics of the task as they interact with the capabilities of the performer; and (3) objective task complexity, defined strictly in terms of the characteristics of the task, independent of the performer. He then identified four sources of objective complexity: multiple paths, multiple desired end states, conflicting interdependence among paths, and uncertain or probabilistic linkages. Campbell (1988), like Wood (1986), proposed complexity should be treated as a function of task characteristics.

A couple of subsequent studies of task complexity surveyed how the construct was used and defined. T. G. Gill and Hicks (2006) identified 13 distinct ways in which task complexity was conceptualized. They organized these into five complexity classes, arguing that any definition that overlapped classes was bound to exhibit inconsistencies. As an example, complexity related to the difficulty experienced by the task performer will likely decrease as repeated instances of the task are performed. In contrast, complexity, defined in terms of the amount of knowledge accumulated by the task performer, tends to increase with experience. Similarly, whether a financial analysis task is performed with or without a computer spreadsheet tool will have a significant impact on the level of complexity experienced by the performer while not necessarily leading to a significant difference in the knowledge required to perform the task.

Liu and Li (2012) presented an impressive systematic inventory of task complexity definitions, identifying 24 different ways the construct had been defined/used. They broke these into three categories: (1) structuralist – based on the structure of the task, (2) interaction – based on the interaction between performer and task, and (3) resource requirement – based on the resources required to perform the task. In their analysis, they expanded Wood's (1986) three task components to six: Goal, Input, Process, Output, Presentation, and Time. They further derived ten dimensions of task complexity: size, variety, ambiguity, relationship, variability, unreliability, novelty, incongruity, action complexity, and temporal demand.

The most recent rethinking of the task complexity construct was proposed by Hærem et al. (2015). Among their most significant contributions were treating task complexity as a function of a network of actors rather than limiting task complexity to tasks performed by a single individual and proposing how the task complexity construct could be extended to multiple levels of analysis. As an example, they used a North Sea counterterrorism (NSCT) task with actors that included boats and planes –

each of which had crews of people. They analyzed the task in terms of the events (acts) and information cues exchanged between actors. Based on this model, they proposed that task complexity should be expected to rise exponentially as the size of the network grows, as opposed to earlier linear models such as Wood's (1986). They also proposed that the task complexity construct could be useful either as an independent variable (input) or dependent variable (output) in organizational research.

A particularly interesting observation made by Hærem et al. (2015) involved the lack of impact that the previous studies of the task complexity construct had on how the construct was operationalized in subsequent research:

> Of the 705 studies in the Social Sciences Citation Index citing either Wood (1986) or Campbell (1988), we found only 39 in which scholars attempted to operationalize task complexity in line with Wood's and Campbell's original definitions (Hærem et al., 2015, p. 448).

To assess if the convergence problem persisted, for the purposes of the present paper, we examined a sample of 50 articles with "task complexity" in the title that were published subsequent to Hærem et al. (2015), drawn from Google Scholar. We used the T. G. Gill and Hicks' (2006) 13 construct scheme to classify usage. We found research applying 12 of the 13 original constructs, with a new construct (heterogeneity) being added. The summary results of our investigation are presented in Table 1, which includes counts and sample quotes. Based on our results, we conclude convergence has yet to occur.

PROBLEMS WITH EXISTING TASK COMPLEXITY DEFINITIONS

Lack of convergence is not alone in frustrating attempts to apply task complexity. Despite the considerable effort that has been made to clarify the construct, there remain challenges that have yet to be fully addressed. We summarize some of them here.

THE TASK STRUCTURE PARADOX

Many of the most influential conceptualizations of task complexity (e.g., Hærem et al., 2015; Wood, 1986) require that the acts, cues, and outputs of a task be well specified to determine task complexity. This works for highly structured tasks. It is not clear that these approaches can be applied to tasks that are very low in structure – such as writing a novel. There are also tasks that can be accomplished in a manner that is either low or high in structure. Consider, for example, the task of competing in the game Jeopardy™. When the player is a human, the problem space is largely unbounded; even the participants are unlikely to be able to specify what elements of their knowledge and experience will ever be applicable. When the player is IBM's Watson™, in contrast, the problem space is necessarily fully structured since the task is performed algorithmically and the available resources are specified in advance.

On the structured-unstructured continuum, low-structure tasks are typically characterized as complex. Limiting task complexity to fully structured tasks would limit the application of task complexity to tasks that, by some definitions, are not very complex.

AMBIGUITY WITH RESPECT TO WHAT CONSTITUTES A TASK

Establishing the boundaries for a task has been a challenge for task complexity research since its outset (e.g., Wood, 1986). Hærem et al. (2015, p. 451) provided an invaluable service by expanding the scope of earlier research, which tended to focus on the individual (limiting its applicability in many contexts). Doing so, however, introduces ambiguity with respect to how a task differs from other definitions, such as those of an activity, a job, a project, and so forth.

Table 1. Constructs from T. G. Gill and Hicks (2006) identified in recent (2016-2022) research sample

Construct (count)	Example quote
1. Degree of Difficulty (18)	"Task complexity represents the level of ease and or difficulty with which employees fulfil their jobs." (Ghani et al., 2019).
2. Sum of JCI or JDS factors (1)	"On the basis of JCM, we define customer task complexity as customer tasks that are rich in variety, identity, significance, autonomy, and feedback." (Gong & Choi, 2016, pp. 1005-1006).
3. Degree of stimulation (2)	"Task complexity is defined as the level of stimulating and challenging demands related to a task." (Jung et al., 2022, p. 2).
4. Amount of work required to complete the task or information load associated with the task (3)	"Indeed, a significant advantage of this task (and CSOPs in general) over tasks that are more commonly studied in group performance settings is that its complexity can be quantified in terms of the run time required by an algorithmic solver to find the optimal solution, allowing us to easily rank task instances by complexity." (Almaatouq et al., 2021).
5. Amount of Knowledge (9)	"Task complexity can be seen as a specific nature of a task that requires extensive and diverse knowledge and skills to complete that task." (Jung et al., 2020, p. 3).
6. Size & 13. Function of task characteristics (3)	"Task complexity dimensions refer to task characteristics that may increase complexity, such as the size of the task, the diversity/variety of tasks, the variability of the working conditions, the interdependence between task elements, the complexity of physical manipulations, the information demands, and so on." (Androulakis et al., 2023, p. 1550).
7. Number of Paths (6)	"As more paths mean more task complexity and fewer paths mean less task complexity, we can explain how task complexity is constructed as a social practice." (Danner-Schröder & Ostermann, 2022, p. 438).
8. Degree of task structure (3)	"Ten definitional complexity dimensions are summarized, i.e., size, variety, ambiguity, relationship, variability, unreliability, novelty, incongruity, action complexity, and temporal demand." (Liu & Li, 2016, p. 11).
9. Non-routineness or novelty of task (3)	"Greater task complexity demands that the jobholder learn and use a variety of skills, which is more cognitively challenging than simply using a limited set of skills repeatedly without the need to learn new skills. Greater task complexity also demands that the jobholder complete the tasks from beginning to end, which is more cognitively challenging than working on one part of the task only." (Zhang et al., 2017).
10. Degree of Uncertainty (9)	"Task complexity is an important determinant of performance in dynamic settings because it leads to changes in task and situational demands and involves uncertainties and shifts in cues that can impact performance when not managed well." (Pasarakonda et al., 2021, p. 921).
11. Complexity of underlying system or environment (6)	"By definition, such tasks are multifaceted and rather unpredictable, often comprising multiple subtasks that are interdependent and necessitate careful alignment." (Oedzes et al., 2019, p. 314).
12. Function of alternatives and attributes (12)	"Task complexity can be defined as the amount of information related to a task an individual has to process when performing a task. Task is considered to be more complex if (1) there are multiple ways to complete it, or (2) has multiple desired outcomes, or (3) there are conflicting interdependence among paths, or (there are uncertain or probabilistic linkage among paths and outcomes)." (Yulianandra et al., 2017, p. 120).
New: Heterogeneity (9)	"From the structuralist perspective, task complexity is reflected by the structure of a task in terms of the number of task elements, the number of sub-tasks, and the variety or diversity of task elements, among others." (Chen et al., 2022).

The Relationship Between Task Quality and Task Complexity

It has long been observed that increased task complexity can lead to higher error rates (e.g., Bronner, 1994). Nevertheless, we were not able to find research specifically addressing the opposite relationship: how changing expectations of task quality impact task complexity.

Part of the problem may stem from how task complexity is operationalized. Hærem et al. (2015, p. 457) rightly object to the fact that task complexity is frequently treated as a binary variable (i.e., high or low). The quality of task performance, however, is similarly likely to exist on a continuum. In an informing task, for example, it is quite possible that an outcome considerably less than "perfect" informing (e.g., a condition in which the client's understanding of a message being conveyed precisely mirrors the sender's understanding) may still constitute acceptable task performance.

Where a task allows for discretion, we would expect that high-quality performance would lead to the emergence of preferred approaches, whereas low-quality approaches would be avoided once discovered – a feedback loop that potentially impacts current and future task performance and, accordingly, task complexity (however defined). Additionally, where discretion in performing the task is available, a performer may willingly trade off some performance quality to keep task complexity at manageable levels. Anyone who has ever had a large stack of student essays to grade in a short period of time has confronted that tradeoff.

The Research-Practice Communication Barrier

If we want our research to impact practice, it is important that our use of terminology be understandable to practitioners. Task complexity presents a challenge in this regard because, in practice, task performers widely perceive task complexity to be the same as task difficulty (Liu & Li, 2012, p. 559). We observed a similar relationship in Table 1, where the difficulty category of construct was the most common based on the count. If we insist on divorcing our definition of the construct from how practice understands it, we create a communications barrier. Understanding the challenges of communications between different communities has long been a central research stream of informing science (e.g., T. G. Gill, 2010).

What is Task Complexity Good For?

A problem with task complexity definitions that has persisted since they were first introduced is the question of the purpose that the construct – however defined – serves. Hærem et al. (2015) discuss task complexity's potential as both an independent variable (i.e., an input) and as a dependent variable (i.e., an output). Their model is vague; however, with respect to the former, what outcomes do we expect when task complexity is present? Most of the remaining attempts to define the construct conceptually focus strictly on the relationship between inputs and resultant task complexity. Interestingly, the most concrete proposition for the impact of task complexity that we were able to find was in the conclusions of Wood (1986, p. 80), who asserts: "Together, these three types of task complexity determine the total complexity of a task *and the resulting knowledge and skills required of individuals for performance of the task*" [italics are ours].

When task complexity is employed in empirical research, the problem is the opposite. Because of the many alternative definitions of task complexity that have been proposed, researchers have a virtual buffet of variables that they can operationalize as "task complexity." The potential threat to rigor presented by this "buffet" is that a researcher could keep trying different operationalizations of "task complexity" until finding one that satisfies desired tests. The subsequent challenge then becomes interpreting what it means when they report that some variable, such as error rate, is a consequence of task complexity.

EXAMPLE: A TASK IN POPPER'S THREE WORLDS

As previously discussed, ambiguity regarding how we view a "task" interferes with our understanding of task complexity. A considerable amount of this ambiguity can be resolved by introducing Popper's (1972) "worlds." We now present this scheme and consider how it could be operationalized, for example, by performing a task like playing a piece on the piano.

THE THREE WORLDS

Under Popper's (1972) conceptual scheme, a phenomenon can be considered from three perspectives, which he refers to as worlds. The three worlds can be described as follows:

- *World 1* is the realm of the natural world. This is the world as it exists. It can be best explained by the studies of natural states and processes such as chemistry and physics. In the context of a task, we can view this in terms of the influences on the task that are external to how the task is defined and performed. These influences are processes and relationships that we do not necessarily understand and cannot necessarily predict – particularly when the many elements of the world interact – and that we cannot control.
- *World 2* is the realm of thoughts and feelings, including the cognitive experiences of humans and animals. In the context of a task, we can think of this world as taking place within the mind and can be treated as distinct from the symbolic processes that we employ from time to time, such as logical reasoning and mathematics.
- *World 3* is the realm of objects created by humans, viz., products of thought. These can range from technologies to scientific theories to art to man-made rules or laws. For our purposes, we treat this world as the symbolic representation of the task.

PLAYING THE PIANO IN THREE WORLDS

To make these three worlds more concrete, we consider an example task: playing a piece of sheet music on the piano. From the perspective of World 3, the task is entirely described by the symbols on the sheet music and the attribute values of the characteristics that define the piano. To establish the complexity of the task, we would likely use input values such as the total number of notes, the average number of notes played simultaneously during each time interval, the variability of rhythms, the number and diversity of notations above the staff, and so forth. The insights of this analysis might help us predict the knowledge and capabilities required to perform the piece. Examining the sheet music might also serve as the basis for estimates of how long it will take to learn the piece from a particular starting point. It might even serve as a basis for predicting the likelihood of errors occurring during a rendition of the piece.

From the perspective of World 2 – what we experience – we previously noted how task complexity is treated as equivalent to difficulty according to some definitions. Depending on the performer's experience, the task of learning a new piece can be perceived as being quite difficult. But this difficulty should decline over time – as anyone who has ever practiced an instrument (or repeatedly performed any routine task) can attest. It will also differ significantly across performers.

The interpretation of task complexity from the perspective of World 1 is less straightforward. Like many art forms, piano playing consists of both technical proficiency (i.e., getting the notes and rhythm right) and artistic interpretation. While the former is largely a prerequisite for adequate task performance, the latter is what distinguishes the competent pianist from the true master. Ultimately, it is how the real world (i.e., World 1) reacts to the performer's playing that will determine whether the approach taken to performing the task is reinforced – and, possibly, mimicked by other performers – or if the performer ultimately decides to find a new line of work.

The challenge presented by World 1 is that for some tasks, such as solving an equation, there is a "right" answer, and we don't necessarily care how the performer gets to it (assuming an acceptable level of resources are expended). For other tasks, such as the previous concert pianist example, finding the sweet spot that leads to exceptional task performance would certainly seem to be an aspect of the task that would contribute to its "real world" complexity.

A THREE WORLDS APPROACH TO TASK COMPLEXITY

With the previous example in mind, we now propose a general framework for viewing task complexity structured according to Popper's three worlds. This framework could be considered a hybrid of the frameworks proposed by Hærem et al. (2015, p. 451) and Liu and Li (2012, p. 564). Like the former, we advocate a single construct approach rather than the latter's approach of separating task complexity into ten dimensions. On the other hand, to achieve relative consistency in how task complexity behaves in different contexts, we operationalize task complexity differently in each of the three worlds.

CHARACTERIZING A TASK

How we define "task" has a significant impact on how we view task complexity. Hærem et al. (2015) advocate operationalizing tasks at different levels, from the individual level all the way up to a task that encompasses a broad mission (e.g., North Sea counterterrorism). We largely agree with this position since each level (e.g., task, job, project, mission, strategy) can ultimately be decomposed into a set of available activities.

We advocate a state-based approach to defining a task. Specifically, we characterize a task in terms of specifying the criteria for two sets of states:

1. *Initial states:* The set of possible states from which task performance can be initiated. These criteria can be very limiting (e.g., the initial task states of "getting to work" might be limited to a specific individual driving from a particular home to a particular job on a particular day and time) or very broad (e.g., the set of initial states may include all possible instances that involve getting to work across all possible individuals and jobs).
2. *End states:* The set of possible states that satisfy the criteria for completing the task or – for ongoing tasks that do not have a defined endpoint (e.g., the NSCT task described by Hærem et al., 2015) – continuing the task.

The state-based approach offers considerable flexibility. For example, if we wanted a task to be performed in a specific manner, we would exclude any end state that was not achieved through the intended process. For our initial state, we might similarly exclude any performers who did not have the prerequisite knowledge to complete the task according to the required procedure. For example, if we wanted to assess the task complexity associated with solving a particular differential equation, we would normally limit ourselves to individuals who had been trained in solving differential equations. On the other hand, if the task were specified as learning to solve differential equations, we might well exclude any individuals who already had that knowledge.

TASK COMPLEXITY AS A LATENT CONSTRUCT

Among the concerns we expressed regarding the current state of the task complexity construct were i) lack of clarity regarding what the construct could be used for, ii) failure to accommodate tradeoffs between performance quality and task complexity, and iii) the communications barrier present when researchers define a construct in a manner significantly different from how it is used in practice. To address these concerns, we propose a common framework that applies to all three worlds of task complexity. The framework consists of six key elements:

- *Task complexity* is proposed to be a latent construct whose level is driven by a collection of *inputs* (that vary by world) and whose presence and level result in a collection of *outcomes*.

- A *familiarity*-based construct, the form of which differs by world, moderating the input-complexity relationship. This moderation can serve to suppress the impact of the inputs on task complexity and can also promote increases in the world's complexity measure.
- A *discretion*-based construct, differing by world, moderating the input-complexity relationship. The construct can either suppress or amplify the impact of the inputs on task complexity. An important influence on the direction of moderation is *feedback* from task outcomes; in this way, task performance can adapt to the quality of performance.

The unifying framework is presented in Figure 1.

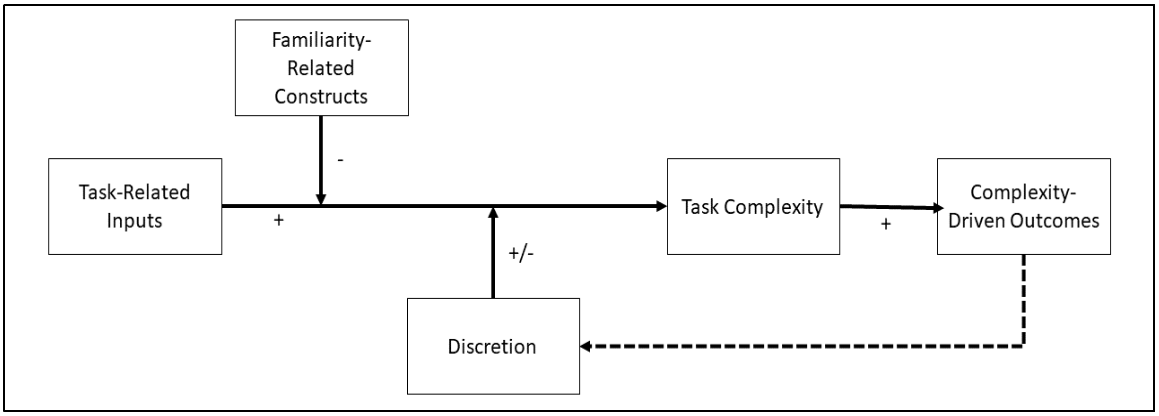

Figure 1. Task complexity organizing framework

WORLD 2: EXPERIENCED COMPLEXITY

Of the three worlds of task complexity, experienced complexity is the world that has evolved least since its early days (e.g., Campbell, 1988). It is also well supported by research on cognitive processes, much of which is quite old – but has stood up well (e.g., Gobet et al., 2001; Miller, 1956; Schneider & Chein, 2003; Shiffrin & Dumais, 1981).

To operationalize experienced complexity, we begin by identifying inputs that could affect task complexity. Since the current paper's objective is focused on rethinking how we frame task complexity (as opposed to identifying new factors impacting/impacted by task complexity), we rely mainly on an existing list of potential complexity sources: Liu and Li's (2012) ten complexity dimensions. To adapt these to our framework, we need to reclassify some of the elements that will tend to decline with repeated performance of task instances: ambiguity and novelty. These are a better fit with the task familiarity construct. In addition, we chose to omit the "action complexity" dimension owing to its recursive nature.

For the experienced complexity-related outcomes, we propose difficulty, level of attention, uncertainty, and error rate. As we noted earlier, in practice, difficulty is often viewed as synonymous with task complexity. We distinguish between the two by acknowledging that difficulty can have sources beyond task complexity, such as the physical demands of the task and distractions. Level of attention is intended to incorporate information processing perspectives on the construct (e.g., Schroder et al., 1967), as task complexity is frequently viewed as a source of cognitive demand (Campbell, 1988). Uncertainty is also perceived to be a consequence of task complexity by several researchers (Liu & Li, 2012). Likewise, prior research has found a significant relationship between task complexity and error rates (e.g., Bronner, 1994).

Under the familiarity construct, we include ambiguity, novelty, and routineness. The first two would negatively impact familiarity, while the routineness of the task would be positively associated with familiarity. The rationale for proposing that familiarity will reduce complexity is grounded in cognitive science. As a task is performed repetitively, the concepts involved become more tightly related, a process referred to as chunking (Miller, 1956), and procedures become increasingly compiled so they can occur automatically (Shiffrin & Dumais, 1981). Both these processes allow the task performer to overcome working memory and attention limits.

The role discretion plays in the experienced task complexity model is particularly significant. One of the challenges confronting task complexity models – particularly those involving complexity as experienced by an individual task performer – is that different instances of a task often involve quite different activities. The result is that outcomes are inconsistent with straightforward models that, for example, predict that increasing the level of input variables to task complexity will lead to increased difficulty, information processing, etc.

The challenge presented by discretion is well illustrated by early experimental research that used an alternative and attributes operationalization of task complexity (Payne, 1976). The researcher provided subjects with a problem based on choosing a rental apartment, manipulating both the number of attributes for each hypothetical apartment alternative and the number of apartments to be considered. Under a typical task complexity model, as alternatives and attributes grew, so would task complexity and, consequently, complexity-driven outcomes. Instead of this straightforward relationship, experimental subjects altered their decision strategies as the number of alternatives and attributes grew. Specifically, subjects reduced cognitive demands by substituting techniques, such as elimination by attributes, for detailed apartment-by-apartment comparisons. Doing so allowed many apartments and attributes to be dismissed with minimal consideration. What allowed this phenomenon to take place was the level of discretion permitted in the experimental task. Similar findings emerged from subsequent research (e.g., Olshavsky, 1979).

In the model we propose, the discretion feedback loop would activate changes to how the task is performed based on expected experienced task outcomes (e.g., difficulty, attention required). For example, if too much attention was being demanded, the loop might signal that shortcuts should be taken (as was the case in the experiment just described). Alternatively, if the error rate was too high or the uncertainty was too great, it could signal a need for a more rigorous approach to the task.

The feedback loop could also influence the level of meta-task activities, such as testing activities intended to improve the performer's understanding of the task. For some tasks, these learning activities may be inseparable from the task itself. For example, a doctor may choose to look up medical research articles in cases where a patient's symptoms inadequately fit with the physician's existing mental models. Our contention is that such learning activities – even if not explicitly required by the task assignment itself – will necessarily impact the task's experienced complexity.

The experienced complexity model we propose is presented in Figure 2. Its applicability is best limited to individual instances of the task. Specifically:

- It is quite possible that very different experienced complexity may result from different initial states.
- How the task will be performed is dependent upon the performer's existing knowledge and on any requirements (e.g., procedures) built into the task specification.
- Because the model is based on cognitive principles, it is not clear that it will generalize beyond the individual to multi-actor situations.

It is also noteworthy that the outcomes of experienced complexity are heavily influenced by the inputs of the task and its familiarity, especially its routineness. We anticipate that the cognitive limits of the individual will result in the application of discretion to alter or abandon the task should its end products (e.g., difficulty, attention) exceed a certain threshold. Thus, no matter how high the complexity-producing potential of the task's inputs, experienced complexity is likely to plateau at a certain level where the performer's cognitive limits have been reached.

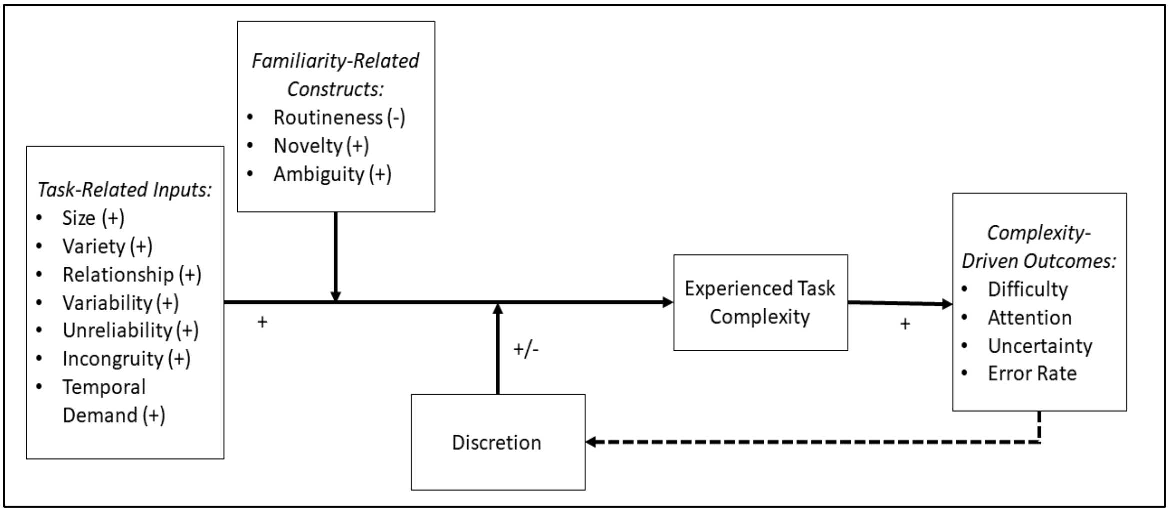

Figure 2. Experienced task complexity model

WORLD 3: INTRINSIC COMPLEXITY

Under World 3, we analyze a task's complexity by looking at the task performance system, which drives the approach that will be employed to perform it. In doing so, we need to limit our consideration of a task to those initial states and ending states that can be performed using the approach we are analyzing. In fact, we are not really analyzing the task itself. Rather we are analyzing the attributes of the system that determines how we will perform the task. Using the terminology adopted by T. G. Gill and Hicks (2006, p. 4), we refer to this system as the task's problem space:

> *Definition:* A problem space is a representation of the cognitive system that will be used to perform a task: "described in terms of (1) a set of states of knowledge, (2) operators for changing one state into another, (3) constraints on applying operators, and (4) control knowledge for deciding what knowledge to apply next" (Card et al., 1983, p. 87).

In practice, assessing the task complexity in terms of a specific problem space is not a significant limitation. On the contrary, nearly every approach to task complexity seeking to quantify task complexity objectively assumes a particular approach to the task. Wood's (1986) component and coordinative complexity depend upon a task organized in a particular way. Campbell's (1988) paths presume the task has specific predetermined paths. Hærem et al.'s (2015) NSCT task assumes a particular approach and network. Naturally, different task instances will activate different areas of the problem space. For that reason, a problem space model is best applied to a collection of task instances and not a single instance. For many task instances, only a small portion of the problem space is likely to be activated.

There are several reasons why a problem space approach to task complexity – which we refer to as *intrinsic complexity* – is worth defining. The first is illustrated by why we might choose to go to a primary care physician as opposed to a nurse practitioner when we feel the onset of a cold. It is quite likely that both will end up providing similar advice. Moreover, the doctor and nurse may well exhibit similar experienced task complexity in performing the task. Where they differ is in the depth and breadth of non-routine issues that we would expect them to be able to diagnose and treat. Stated another way, the doctor – by virtue of education and experience – is likely to have a substantially expanded problem space when compared to the nurse. Even though very little of that problem space is likely to be activated in our case, we may feel more comfortable knowing the breadth of diagnosis task instances that *could* be accommodated if needed.

A second justification for defining intrinsic complexity is that it overcomes a significant limitation of experienced complexity. In the experienced model, changing a task by employing a tool – such as a computer spreadsheet – can dramatically affect the performer's experience. In the intrinsic complexity model, the use of the spreadsheet to perform computations that were previously done manually would have little or no impact on the symbolic structure of the problem space or its intrinsic complexity. Similarly, there is no conceptual barrier to representing a problem space symbolically that extends across multiple individuals and systems. Because it does not rely on the individual's reaction to the task (as experienced complexity does), intrinsic complexity is much easier to apply at different levels. Even at the individual level – the domain of experienced complexity – intrinsic complexity can potentially be applied. For example, the task of an individual preparing income taxes using tax preparation software can be visualized as a problem space that incorporates both the knowledge of the task performer and that embedded in the software. Alternatively, we could look at the task strictly from the user's perspective, limiting the problem space to the knowledge/rules/operators needed to operate the software and acquire its inputs (without necessarily having any detailed knowledge of the tax code).

Another benefit of defining intrinsic complexity is that there is a large body of research that has investigated similar concepts in the world of information systems under headings such as software complexity, systems analysis and design, and software testing. A variety of techniques – such as function point complexity (e.g., Xia et al., 2008), cyclomatic complexity (Ebert et al., 2016), Kolmogorov complexity (Li & Vitanyi, 1993), and many others – could potentially be adapted to a problem space that extends beyond a single information system.

Intrinsic complexity is not without its drawbacks. Although most of Liu and Li's (2012) complexity dimensions seem best suited to experienced complexity, both Wood (1986) and Campbell (1988) provide characteristics that would seem likely contributors to intrinsic complexity: number of task components, number of acts that must be coordinated, multiple paths (which can either contribute to or reduce task complexity; Campbell, 1988, p. 43), multiple desired end states, conflicting interdependence among paths, and uncertain or probabilistic linkages. Hærem et al. (2015) also provide a very rich example of how intrinsic complexity could be computed, its main limitation being that it is most readily applied to a network of communicating actors. That model would be much more difficult to adapt to tasks where most of the processing takes place within the minds of individuals.

Proposing the expected outcomes of intrinsic complexity is significantly more challenging. Because a problem space can apply to a broad range of tasks – some requiring minimal information processing, some requiring much greater effort – the types of outcomes associated with the instance-specific experienced complexity construct are unlikely to generalize. Because many of the proposed inputs will impact how large a complete description of the problem space would be (an analog to Kolmogorov complexity), we feel confident in predicting that intrinsic complexity could impact the time it takes to learn the task (or implement the problem space as an information system). As proposed in Wood's (1986) earlier-mentioned conclusions, it could also predict the prerequisite knowledge and skills of the individuals who would perform the task. Drawing upon software complexity findings, it could also be predictive of the number of flaws in the problem space that could produce undesired outcomes (e.g., bugs in a system).

Assessing the role played by familiarity factors within intrinsic complexity raises several issues. Whereas experienced complexity tends to decline predictably with repetitions, we would expect some learning to occur as different task instances are handled by the problem space. In consequence, absent a significant restructuring of the problem space, we would expect that intrinsic complexity could grow incrementally with the task's continuing performance across various instances.

The greatest familiarity challenge comes from task structure, sometimes identified as a source of complexity (Liu & Li, 2012). We define structure in terms of our problem space. For a fully structured task, every task instance contained in our initial set can be completed within the boundaries of the problem space defined for the task. In an entirely unstructured task, none of the instances in our initial state set can be fully handled using a predefined problem space. Between the two extremes exists a continuum where some of the initial instances can be accomplished within the boundaries of the problem space, some can be partially completed, and some cannot be addressed. High-structure tasks will be those where most instances can be handled within problem space; low-structure tasks would frequently require task activities beyond the defined problem space boundaries.

Just because a task cannot be completed within its well-defined problem space does not mean the task cannot be accomplished. Rather, we must accept that for low-structure tasks – such as writing a novel – we won't be able to determine intrinsic complexity with any accuracy. We simply cannot identify all the resources and activities that our set of initial task instances will require in advance. Moreover, if we were to try to guess at intrinsic complexity, the value would likely be quite large. For example, almost everything an individual has experienced, knows, or believes could potentially contribute to the aforementioned novel. Of course, our estimate would also vary considerably across performers; we all differ substantially in what we have experienced, know, and believe. Nevertheless, the need for knowledge/capabilities outside of the structured problem space would necessarily add to the intrinsic complexity computed for the problem space itself. Thus, the perspective that lack of structure contributes to task complexity is consistent with our model. We would also usually expect structure to increase (i.e., lack of structure decrease) with repeated performance of diverse task instances, potentially reducing intrinsic complexity until the point where the task is fully structured.

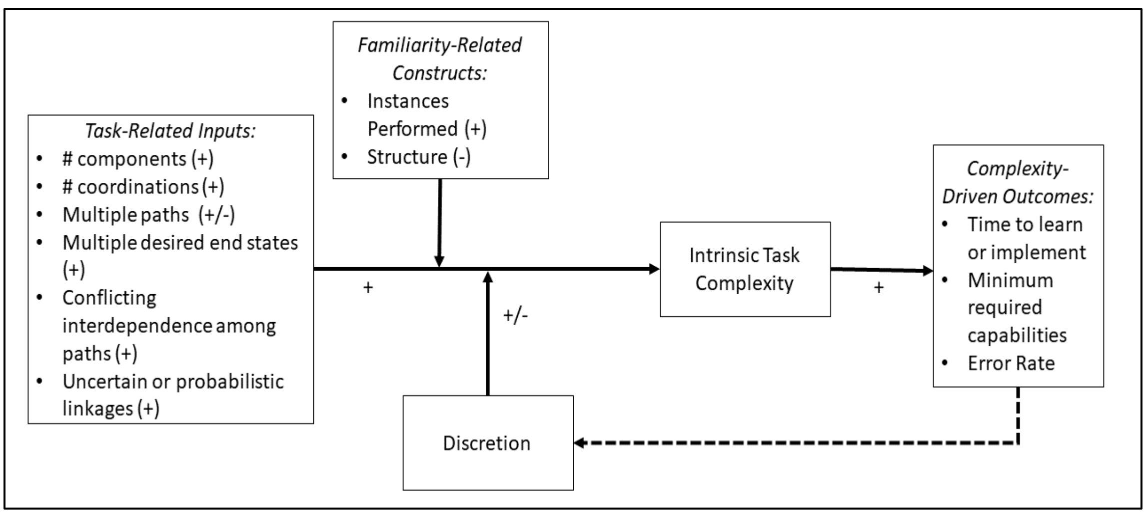

Figure 3. Intrinsic task complexity model

The model proposed for intrinsic complexity is presented in Figure 3. Whereas our experienced complexity model was best evaluated for a single instance from the task's initial set, the intrinsic complexity value is largely determined by the elements of the process through which the task runs from the initial state to the end state. We need to know the problem space in advance to compute it.

Intrinsic complexity is applicable to all the tasks that can be completed using the same problem space. It has an important limitation, however. Where two entities (e.g., individuals, teams, organizations, etc.) apply different problem spaces to the same task, there is no reason to believe that the intrinsic complexity for one entity will be the same as it would be for the other.

WORLD 1: EXTRINSIC COMPLEXITY

The final world of task complexity captures how the task interacts with the external environment. As we noted earlier, the existing task complexity literature has paid scant attention to how the quality of task outcomes impacts the task's complexity (although it has considered the impact of complexity on quality). For some tasks, the impact is likely to be minimal; for others, it may represent the principal source of the task's complexity (however we choose to define it). To illustrate, consider two tasks that might appear superficially similar: painting a scene by numbers and painting a scene on a blank canvas. Although the physical activities in both tasks are going to appear similar (i.e., mixing paints to get a desired color, applying the paint to canvas), the latter task will entail indeterminant intrinsic complexity (owing to its low structure). For our purposes here, however, the most striking difference between the tasks is how the task end products are likely to be valued. We may reasonably predict that the paint-by-numbers scene will have negligible monetary value and might earn a place on the painter's bedroom wall (provided the painter is a pre-teen). The original scene, in contrast, could potentially have a huge variation in value, ranging from the negative (i.e., what it costs to dispose of the spent canvas) to a price at auction of over $100 million. What is particularly interesting about this range is how difficult it is to make an accurate estimate when the only artifact available is the task product itself (as opposed to knowing who the artist is and what similar pieces have sold for).

As the painting example suggests, for many tasks, the quality of task outcomes can be quite important in assessing task performance. For some tasks (e.g., paint by numbers), the determination is relatively straightforward. For others (e.g., original landscape), the highly subjective nature of the assessment makes accurate determination nearly impossible. Because the value of the output is largely driven by real-world forces external to the task itself, we refer to this source of complexity as *extrinsic complexity*.

None of the reviews we examined explicitly addressed extrinsic complexity as we have characterized it. There is, however, a substantial literature drawn from evolutionary biology (e.g., Kauffman, 1993) that has also been applied to the management task of strategy determination (e.g., Levinthal, 1997; Levinthal & Warglien, 1999). In this approach, an entity's state – end-state, for our purposes – is described with a series of attributes. Each possible state is associated with a quality-related value referred to as *fitness*. The complete set of mappings between state and fitness is referred to as a *fitness landscape*. The nature of the relationship between attributes and fitness determines the shape of the landscape. In a fully decomposable (i.e., low complexity) landscape, fitness is determined by a simple sum of the relative contribution to fitness of each attribute – analogous to how each question contributes to the overall score on a multiple-choice test. The result produces a landscape with a single fitness peak. In a maximally complex landscape, fitness is determined by each unique combination of attributes, and many local peaks likely exist. In the landscape of published fiction, the combination of individual words in each novel can be viewed as its author's attempt to achieve an individual peak.

To illustrate the difference in complexity associated with the two landscape extremes, consider how much information a task performer would need to discover the "optimal" output for a task with 20 attributes that can each be 0 or 1. For the fully decomposable landscape, we would need to know 20 values – the marginal contribution to the fitness of each attribute. For the maximally complex case, in contrast, there are over a million (2^{20}) possible unique combinations, each of which would have to be examined. Naturally, we would expect most real-world landscapes to exist on a continuum between the two extremes. Kauffman (1993) proposed a tunable model – the NK-landscape – that can be used to simulate different levels of complexity.

Given its biological origins, it is not surprising that the fitness variable is driven by two factors: the entity's ability to survive and the entity's ability to reproduce. We can adapt these to the context of the fitness of a particular problem space for a task instance. In this context, a high fitness value would encourage continued application of the same problem space for similar task instances (survival). The approach might also be copied by others seeking to improve their own outcomes or extended to other task sets (reproduction). Alternatively, a low fitness value might lead the performer to search for another problem space.

Extrinsic complexity presents static and dynamic challenges. The principal sources of static extrinsic complexity are the number of attributes that contribute to the fitness of the task's end state and the number and strength of interactions associated with the fitness relationship (roughly corresponding to N and K, respectively, in the NK-landscape model). Both contribute to the complexity of the landscape, although the K value is particularly important in practical terms. This complexity manifests itself in the presence of many local fitness peaks. These peaks can have the effect of terminating an entity's incremental search processes even if a given peak has a significantly lower fitness value than that of other attainable peaks. What makes this particularly problematic is the empirically observed tendency of complex landscapes to exhibit power law distributions in outcomes (Taleb, 2007). The practical implication of this is that as the landscape becomes more extrinsically complex, the potential cost of missing high-value combinations can be very high. Moreover, even seemingly minor changes can have a large impact on fitness. For example, the huge differences in the value placed on different violins cannot be explained entirely based on sound quality (e.g., Fritz et al., 2017).

The dynamic element of extrinsic complexity is driven by changes to the fitness landscape. These changes can result from entities repositioning themselves on the landscape (e.g., the emergence of a new category of literature that attracts many new authors). Related to that is the rate at which entities can adapt. For example, environments that require large long-term investments (e.g., the power industry) may exhibit more stable fitness landscapes than those that can change quickly (e.g., software apps). Dynamic fitness landscapes can also result from interactions with co-evolving systems. For example, advances in AI may lead to new art forms enabled by the technology that, in turn, spurs further technological advances aimed at supporting the growing needs of digital artists.

Broadly speaking, landscape ruggedness is likely to be pronounced in what is also referred to as "high-velocity environments" (Bourgeois & Eisenhardt, 1988), described as follows:

> … those in which there is rapid and discontinuous change in demand, competitors, technology and/or regulation, such that information is often inaccurate, unavailable, or obsolete (p. 816).

Such landscapes make it very difficult to find the sweet spot for task outcomes, particularly using analytical means. Such landscapes are argued to be particularly susceptible to herding behavior, referred to as homophily (e.g., T. G. Gill, 2012). Conceptually, this translates to identifying a high-fitness entity and then attempting to replicate, as closely as possible, its attribute values. For example, the film industry exhibits all the characteristics of a very rugged landscape, particularly with respect to its large distributions of outcomes and the difficulty of predicting whether a novel film will pay back its investment. One way the huge investment risk can be reduced is to produce films that are as similar as possible to films that are already proven to be successful. Thus, we see the emergence of sequels, franchises, and film "universes."

With respect to the familiarity-related constructs in the model, the impact is limited. Because extrinsic complexity deals with complexity related to the external environment, the ability of an individual task-performing entity to impact complexity is limited. Nevertheless, being able to observe the behavior and fitness of other task performers could have some impact. For example, observability has been found to increase the rate of adoption of innovations (Rogers, 2003, p. 222). Conceptually, where the fitness of other tasks is readily observable, a performer's willingness to consider changing peaks is likely to be higher. Particularly in a competitive landscape, we might expect that entities redistributing themselves will impact the broader state-fitness relationships (e.g., as certain states become crowded). The effect of distribution on the landscape is predicted to be particularly pronounced in environments where network effects are present (T. G. Gill, 2012, p. 76), meaning that fitness grows as more entities occupy a particular region of the landscape.

The presence of discretion is unlikely to exert much impact on extrinsic complexity because the individual task performer is likely to have little influence on the fitness landscape. Discretion could, however, have a significant impact on task priorities. Because the relationship between a task end state and its corresponding fitness becomes nearly impossible to assess analytically under high extrinsic complexity, the entity must experiment to assess possible changes to end state attributes. Such experimentation can occur in two directions. It can occur adjacent to the entity's current state; this process will ultimately lead to discovering a local fitness peak. Alternatively, the entity can observe other entities performing the task and imitate them. This may involve changing multiple attributes simultaneously, effectively attempting a jump across the landscape to another perceived fitness peak. Both strategies seem less risky than a jump to an unexplored region. The choice between incremental experimentation and taking a large jump strongly parallels the issues related to choosing a balance between exploitation and exploration (e.g., Gupta et al., 2006).

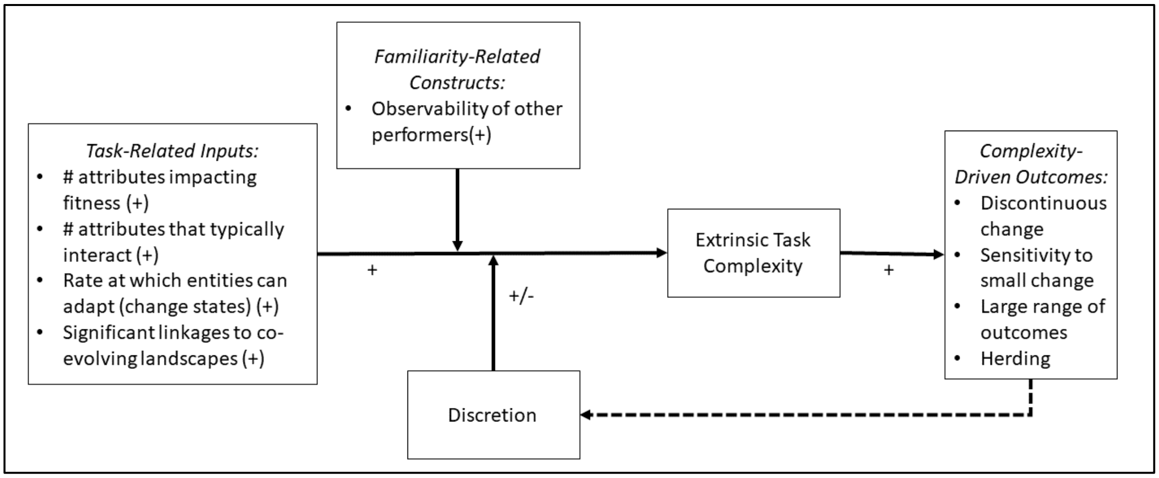

Figure 4. Extrinsic complexity model

The extrinsic complexity model is presented in Figure 4. It differs from the other models in that it places very few restrictions on how tasks are defined or performed. Indeed, to understand the underlying landscape, it is beneficial to include as many different approaches (e.g., possible problem spaces) as possible. It is also the model that affords the least ability to influence the task complexity construct. Rather, the purpose of the model is to allow the performer to better understand the relationship between task performance and task outcomes, along with dynamics likely to be experienced over the course of performing the task.

SUMMARY TABLE

Table 2 summarizes and contrasts the three worlds of task complexity.

Table 2. Summary of three worlds of task complexity

Characteristic	Experienced	Intrinsic	Extrinsic
Task domain considered	Individual task instance and human performer	All task instances performed using a specific problem space	All task instances
Principal focus	Task inputs	Task processes	Task outcomes
Inputs	Characteristics of the specific task instance	Characteristics of the problem space	Characteristics of the environment of the task
Outcomes	Difficulty, Attention, Uncertainty, Error rate	Time to learn or implement; Minimum required capabilities; Error rate	Environment characteristics: Discontinuous change; Sensitivity to small change; Large range of outcome values; Herding
Effect of repeated performance	Reduces complexity substantially	Most likely to increase complexity incrementally	Complexity is largely unaffected
Application of task discretion	Manage cognitive demands and enhance performance	Modify problem space to improve performance and increase structure	Balance exploitation and exploration

DISCUSSION

We now consider three specific questions raised by the framework we have proposed: (1) How do the different worlds of task complexity relate to each other? (2) What are the implications of the proposed framework for researchers? (3) What are the implications of the proposed framework for practice?

RELATIONSHIP BETWEEN TASK COMPLEXITY WORLDS

Although task complexity itself is described differently in each of the three worlds, that does not mean that the worlds are unrelated. Based on our analysis, however, the relationships are not necessarily straightforward.

Intrinsic x experienced

It would be easy to propose that high intrinsic complexity should lead to similarly high experienced complexity. Arguments for such a relationship would be based on the expectation that high intrinsic complexity problem spaces are likely to include many control processes (e.g., rules, branches); such processes tend to resist becoming automatic (Shiffrin & Dumais, 1981) over time and would therefore be expected to place high cognitive demands on the performer. Unfortunately, this relationship will be violated frequently for two reasons already mentioned:

1. *Individuals have bounded working memory and attention.* Regardless of the intrinsic complexity value, experienced complexity – as we have defined it here – will tend to be limited to a certain level for a particular individual.
2. *A problem space can extend across multiple actors, including non-human actors.* For example, in our previous scenario of individuals adopting tax preparation software, the complexity experienced by the performers in preparing their taxes may decline, while the size of the task problem space may grow owing to rules and knowledge embedded in the software.

Perhaps the most interesting linkage between experienced and intrinsic complexity involves the previously mentioned task structure. The lack of structure can be expected to increase complexity in both worlds and similarly, the value is expected to decline in both cases as more instances of the task are performed. Here, however, the impact may be dissimilar. The increasing structure should lead to declines in experienced complexity; for intrinsic complexity, it would move the construct from being largely indeterminant for the task to one that better reflects the full range of task instances.

Intrinsic x extrinsic

Extrinsic complexity, being largely a function of the environment, will be difficult for an individual performer to impact. In contrast, the characteristics of high extrinsic task environments – multiple fitness peaks, power law distributions of outcomes, discontinuities in behavior, herding behaviors – will demand the performer maintain resources that support adaptation if it is to survive (i.e., exhibit acceptable fitness). These characteristics would increase intrinsic complexity by requiring that meta-task activities – such as research, learning, experimentation, and observation of other performers – be incorporated into the problem space. As noted earlier, such activities could support either exploration or exploitation, as well as the balance between the two.

Extrinsic x experienced

As was the case for intrinsic complexity, the relationship between extrinsic and experienced complexity is posited to flow mainly from the former to the latter. The ruggedness and velocity of the task environment should exhibit a particularly strong impact on the novelty and ambiguity of the typical task instances encountered, as well as potentially impacting nearly all the other task inputs. This impact may affect the variety of task instances that a typical performer encounters, affecting the average of experienced complexity across instances. In balance, we would expect growth in extrinsic complexity to lead to higher experienced complexity (once again, governed by cognitive limits).

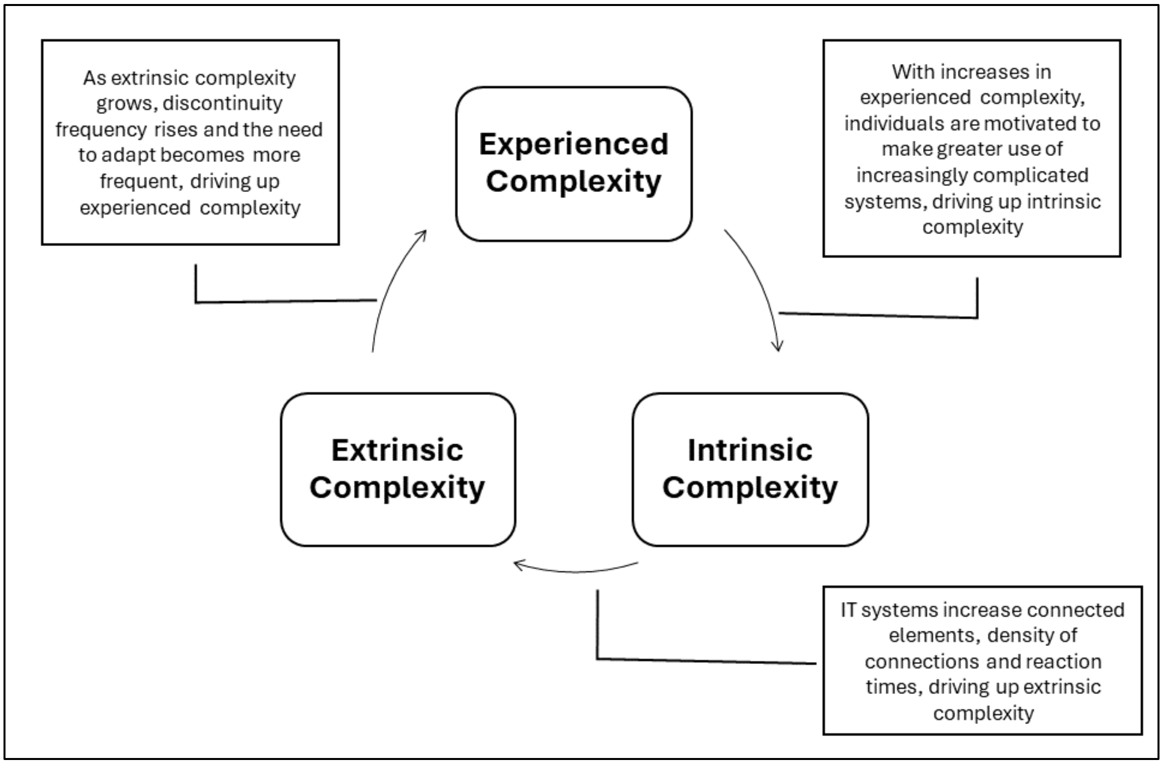

Figure 5. The IT-driven complexity cycle (T. R. Gill & Gill, 2024, p. 9)

Experienced x intrinsic x extrinsic

It has recently been proposed that the three worlds of task complexity might, in the presence of IT, interact to form a cycle (T. R. Gill & Gill, 2024). The nature of the proposed cycle, illustrated in Figure 5, applies when IT is used to alleviate uncomfortably high experienced complexity. The transfer of task activities to IT results in changes to the problem space that generally leads to increased intrinsic complexity. These changes can also lead to increasing numbers of connected system elements, density of connections, and reaction speeds – all common consequences of IT adoption in a connected world. These changes to the task system (and co-evolving systems), in turn, change the behavior of the external environment – tending to increase extrinsic complexity. As a result, we may expect to see the system behaviors typically associated with extrinsic complexity (e.g., punctuated equilibrium, power law variations in system behavior and fitness, turbulence) increasing in magnitude and frequency. These behaviors, in turn, are likely to increase the experienced complexity of the task performers, who are then motivated to enlist the aid of additional IT. And the cycle continues.

Implications for Researchers

There are several potential implications of our framework for researchers seeking to investigate task complexity. First, each of the three world models of task complexity could be translated into propositions relating complexity inputs to complexity outcomes. While we concede that many of these would require considerable thought to operationalize, we think they still represent a step forward from much of the conceptual research that proposes a task complexity construct but is vague with respect to what predicted outcomes the presence of task complexity (however it is defined) lead to.

We also believe that existing research has largely ignored how familiarity, discretion, and meta-activities, such as learning, interact with task complexity. We have argued that these are critical to understanding task complexity dynamics in all three worlds. We have also proposed that they can be incorporated into a model as moderating constructs between task inputs and their resulting task complexity.

Finally, by incorporating the extrinsic complexity construct into our framework, we offer a path toward investigating real-world impacts on task complexity. As implied earlier in our "task structure paradox," one barrier to existing task complexity research may be that the set of fully specified tasks for which task complexity can be rigorously studied is likely to consist of relatively simple tasks (however we choose to define "simple") compared to those that are driven by dynamic environments. The study of extrinsic complexity offers an alternative conceptual scheme that researchers could apply.

Implications for Practice

We admit up front that in proposing how an abstract conceptual framework is likely to impact practice, researchers are afforded the rare opportunity to engage in writing fiction. In that spirit, rather than offer up a series of abstract domains where the three worlds of task complexity might be applicable to practice, we walk through a single informing task likely to be familiar to many readers: determining how credit is allocated between co-authors of a paper. This task was inspired by the (ludicrous) requirement (at the authors' institution) that faculty going up for promotion and tenure specify their estimated contribution in percentage terms for each article they co-authored.

To set up our hypothetical example, let us imagine that an article was the result of a collaboration between a doctoral student, a major professor, and a senior professor. The article was created in the following manner:

1. The major professor comes up with an interesting research question emerging out of her research stream over the past decade.
2. The major professor presents it to her doctoral student, along with a list of about a dozen articles that she believes are relevant. The student studies these articles and agrees to participate in the research.
3. Under the major professor's direction, the doctoral student performs a literature search and drafts the background and method sections of the paper. The major professor revises these significantly.
4. Under the major professor's guidance, the doctoral student develops and administers a survey. The two work together to perform the statistical analysis of the data and write the results section. The doctoral student drafts the discussion and conclusions sections, which are then significantly rewritten by the major professor.
5. Recognizing that the research has significant potential, the major professor enlists the aid of a senior professor who has published extensively and has previously served as a senior editor at the premier journal that they have targeted for the submission. The senior professor makes significant changes to the paper's tone and reorganizes some of the discussion but leaves the results largely untouched.
6. The paper is submitted to the targeted journal and receives a revise and resubmit. All three work together on the first and subsequent revision, after which the paper is accepted.

The question we now pose is: "What is the percentage of contribution from each co-author?" Or, more simply, "Who should be the lead author?"

If we were to address this question in terms of task complexity, each world could easily lead us to a different answer. If we were to allocate credit based on experienced complexity, the doctoral student would be allocated the lion's share of the credit based on (2), (3), and (4). In contrast, considered from the perspective of intrinsic complexity, items (1), (2), (3), and (4) imply that the major's professor's command of the topic area is largely responsible for most of the shared problem space.

Under an extrinsic complexity perspective, the analysis gets trickier. At most institutions, lists of journals – such as the UTD 24 and Australian Business Dean's list – are used to evaluate the so-called quality of articles. At such institutions, the career impact of publishing in a "premier" journal versus a journal that is merely well respected can be huge. Consequently, premier journals tend to have very low acceptance rates – often under 5%. Studies of reviewer ratings done in premier journals (e.g., Starbuck, 2003, 2005) have also demonstrated that consensus between reviewers is not particularly high. Based on these observations, for the purposes of our example, we will assume that the proven ability to navigate the peer review process and move a manuscript to acceptance and publication is an exceptionally valuable (and rare) skill. In many ways, it is analogous to the unique talent that distinguishes the previously described concert pianist from the talented amateur. Moreover, in high extrinsic complexity environments, even small changes in task performance can produce dramatic changes in fitness owing to their participation in interactions. Our conclusion: if the individual's contribution to the fitness of the task is critical, the senior professor's role in the process might be judged as the most significant.

Although the paper authorship example was formulated based on the likely readership for this article, the approach described could be generalized to how recognition/rewards are assigned to many types of tasks. For tasks where intrinsic and extrinsic complexity are low, experienced complexity would be the key driver. Direct productivity measures, which would be expected to grow as tasks become more automatic with practice, could then be rewarded. For tasks where intrinsic complexity is high and extrinsic complexity is low, task knowledge is key. In consequence, measures that reflect the likely size of the individual's task problem space – such as relevant graduate degrees and seniority – might warrant additional compensation. Where the task's extrinsic complexity is high, indicators such as the individual's track record with similarly complex tasks, creativity, and adaptability might be the best predictors of high fitness performance (and most appropriate for rewarding/recognizing).

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Any research that attempts to synthesize and rearrange a large body of research is subject to obvious limitations. In assembling the three-world model, we made some assumptions that will doubtless prove – in retrospect – to be ill-advised. Rather than dwell on these, we now turn to some of the concerns we feel are most significant and, therefore, most likely to benefit from future research.

Chief among these is whether it makes sense to look for a single complexity construct, as Hærem et al. (2015) advocated, or to establish a series of separate complexity dimensions, as Liu and Li (2012) chose to do. Our perspective is that since complexity is often a consequence of interactions, each time we break a construct into separate components/dimensions, we run the risk of creating separate variables whose values do not, on their own, tell us very much; only in combination with other variables do they exert impact – the very source of extrinsic complexity. Nevertheless, we felt the need to define three worlds because the complexity behaviors were so different (e.g., as shown in Table 2). However, within each world, a single complexity construct would be preferable. In the future, however, empirical research might indicate that different combinations of inputs are required to better predict different aspects of task outcomes (e.g., time to learn vs. error rate) as opposed to capturing them all with a single complexity construct. In that case, it might make sense to establish different flavors of task complexity within each world tuned to different complexity outcomes.

A further limitation of our research is that we cannot assert, with complete confidence, that the latent task complexity constructs in each of the three worlds is a "real thing," as opposed to being merely a shorthand way of naming the relationship between each world's inputs and outputs. If subsequent research were to operationalize the inputs and outputs of a world's task model, we might be able to make the case for latency statistically using techniques such as structural equation modeling. But we are a long way from being able to accomplish that. Moreover, some of the constructs we have incorporated – particularly discretion and familiarity – are proposed to operate in qualitative ways, such as influencing path selection and directing performer resources toward learning. Additional theory development would be needed to accommodate these in a manner suitable for formal hypothesis testing.

CONCLUSIONS

Our hope is that the proposed three-world framework will assist both research and practice in making sense of task complexity. In constructing the framework, we drew heavily on past research. Our "experienced complexity" world is nearly identical to Campbell's (1988); our intrinsic complexity is a refinement of the objective complexity variations proposed by Wood (1986), Campbell (1988), T. G. Gill and Hicks (2006), and Hærem et al. (2015). While our treatment of extrinsic complexity is quite novel in the task space, it has strong roots in the treatment of complexity in other domains (e.g., T. G. Gill, 2012; Kauffman, 1993; Levinthal, 1997).

Despite these similarities, we have introduced some clarifications and enhancements that we believe are quite beneficial to understanding task complexity. In particular, the use of a common framework to model complexity in each world is novel, as is our treatment of familiarity and discretion – both of which have the potential to address ambiguities in past complexity research.

We fully agree with Hærem et al.'s (2015, p. 447) contention that task complexity is becoming "an increasingly relevant construct." But until our mutual understanding of the basic nature of the construct converges – which it has yet to do – researchers will have difficulty investigating task complexity, and practice will be challenged in putting it to use. Our hope is that the present research will help both communities move forward.

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