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INFORMATION TECHNOLOGY AND THE COMPLEXITY CYCLE

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ABSTRACT

Aim/Purpose	In this paper we propose a framework identifying many of the unintended consequences of information technology and posit that the increased complexity brought about by IT is a proximate cause for these negative effects.
Background	Builds upon the three-world model that has been evolving within the informing science transdiscipline.
Methodology	We separate complexity into three categories: experienced complexity, intrinsic complexity, and extrinsic complexity.
	With the complexity cycle in mind, we consider how increasing complexity of all three forms can lead to unintended consequences at the individual, task and system levels. Examples of these consequences are discussed at the individual level (e.g., deskilling, barriers to advancement), the task level (e.g., perpetuation of past practices), as well as broader consequences that may result from the need to function in an environment that is more extrinsically complex (e.g., erosion of predictable causality, shortened time horizons, inequality, tribalism).
	We conclude by reflecting on the implications of attempting to manage or limit increases of complexity.
Contribution	Shows how many unintended consequences of IT could be attributed to growing complexity.
Findings	We find that these three forms of complexity feed into one another resulting in a positive feedback loop that we term the Complexity Cycle. As examples, we analyze ChatGPT, blockchain and quantum computing, through the lens

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	of the complexity cycle, speculating how experienced complexity can lead to greater intrinsic complexity in task performance through the incorporation of IT which, in turn, increases the extrinsic complexity of the economic/technological environment.
Recommendations for Practitioners	Consider treating increasing task complexity as an externality that should be considered as new systems are developed and deployed.
Recommendations for Researchers	Provides opportunities for empirical investigation of the proposed model.
Impact on Society	Systemic risks of complexity are proposed along with some proposals regarding how they might be addressed.
Future Research	Empirical investigation of the proposed model and the degree to which cognitive changes created by the proposed complexity cycle are necessarily problematic.
Keywords	complexity, task complexity, information technology, homophily, punctuated equilibrium, systemic risks, information overload, fitness, rugged landscape, unintended consequences

INTRODUCTION

Where would we be without information technology? IT has become exponentially more powerful and elaborate over the last fifty years, yielding countless benefits, and allowing us to attain a level of efficiency vis-à-vis space, time, and effort hitherto inconceivable. IT has also provided us with more options and forms of recreation and socializing. It has given society the ability to better respond to events—the ability to work and learn from home during the COVID-19 pandemic being a recent example.

Despite its myriad benefits, there has also been increasing recognition of many possible unintended consequences of the ubiquitous presence and use of IT. For example, using machine learning algorithms, AI can detect the characteristics associated with successful hires far more efficiently than a human ever could. Unfortunately, these algorithms can be equally efficient in replicating the prejudices and unconscious biases of past human performers (O'Neil, 2016).

Numerous other examples of unanticipated negative consequences of IT exist, across a wide spectrum of effects. The list includes job deskilling (Braverman, 1998; Faik et al., 2020), loss of privacy (Clarke, 2016; Meingast et al., 2006), anxiety/unhappiness (Bawden & Robinson, 2009; Salo et al., 2022), vulnerability (Nawir et al., 2016), dependency (Shu et al., 2011), inactivity/obesity (Fotheringham et al., 2000), loss of competency (Braverman, 1998), and both inequality (e.g., the digital divide; Aanestad et al., 2021; Autor et al., 1998), and perceived inequality (Turel, 2021).

The sheer diversity of these examples raises this question: are the negative effects of IT largely independent or are they related? In this paper, we propose a conceptual scheme called the "complexity cycle," arguing that many of these effects have a common thread. The scheme, based on three distinct forms of task complexity, argues that the introduction of IT frequently leads to changes at the local (individual task) level that contribute to changing broader system levels (e.g., the economic environment) that eventually feed back to the local level and motivate further changes.

We begin by presenting a broad definition of what constitutes a task. We then describe three forms of task complexity – experienced complexity, intrinsic complexity, and extrinsic complexity – drawing from both complexity theory and IS research pertaining to complexity. We next consider how the three forms of complexity interact with each other. The result is a hypothetical positive feedback loop that we refer to as the *complexity cycle*.

Using the complexity cycle as our conceptual framework, we then consider some examples of how different information technologies might act upon the cycle. The specific technologies we consider are ChatGPT (standing in for generative AI as a whole), blockchain, and quantum computing. We argue that the first two can impact the cycle incrementally, whereas the last of these could lead to a discontinuous change in the economic/technology environment though its potential impact on privacy and security.

Based on the predicted behavior of the cycle, we then consider a variety of unintended consequences that could result from the ongoing changes produced by the proposed complexity cycle. Potential consequences are proposed at the individual level (e.g., deskilling, barriers to advancement), the task level (e.g., perpetuation of past practices), the broad system level (e.g., erosion of predictable causality, shortened time horizons, inequality, tribalism). We then discuss how this proposed conceptual scheme might allow us to better anticipate and manage the challenges of task changes accompanying the introduction of IT and the potential implications for informing science.

REVIEW OF RESEARCH

In this section, we review relevant elements of task complexity theory that are the foundation of the ideas presented in this paper.

We conclude the section by considering research that specifically deals with task complexity's relationship to information systems.

TASK COMPLEXITY THEORY

Before beginning this review, we acknowledge that many meanings have been proposed for the "task complexity" construct (Hærem et al., 2015), and the more general concept of "complexity" has been applied to individual thinking in many ways, including "complex thinking", "complexity thinking" and "complex systems thinking" (Teixeira de Melo et al., 2020, p. 167). For our purposes, however, we will employ a lens that considers task complexity in three ways: as it is experienced by an individual task performer (experienced complexity), as it describes the requirements and activities of the task in symbolic terms (intrinsic complexity), and as it characterizes the structure and behavior of the environment in which the task is performed (extrinsic complexity).

What is a task?

To understand task complexity, we must have a working definition of what constitutes a task. For the purposes of this paper, we define a task as having three elements: 1) a set of allowable starting points, 2) a set of acceptable ending points, and 3) a set of rules that specify or limit how the performer can transition from start to finish. This definition, adapted from research related to the informing task (Gill & Mullarkey, 2017), allows most intentional activities to be characterized as tasks. It is also agnostic with respect to how the task is performed—provided such performance is consistent with the specified rules, which may either be very specific (e.g., tasks offering little or no discretion) or which offer little or no guidance on how to achieve an end state. For example, individuals might meet the requirements of the task of "playing a game of chess" regardless of whether they win or lose the game. On the other hand, were those same individuals to cheat (i.e., violate the rules) during the game, then they would not have performed the task.

Having flexibility in defining a task is critical to unwinding the ambiguity of what is meant by task complexity—an ambiguity that has been widely observed (e.g., Campbell, 1988; Hærem et al., 2015). One way to resolve this ambiguity is to recognize that the task complexity construct has been used to describe tasks at three different levels: in terms of its effects on the individual (experienced complexity), in terms of the objective properties of the task itself (intrinsic complexity), and in terms of how the task interacts with the environment (extrinsic complexity; Gill & Mullarkey, 2017). Each of these levels is related; nevertheless each requires us to think about a task in a different way.

Experienced complexity

The first type of complexity, *experienced complexity*, takes place within the mind of the task performer. Originally described by Campbell (1988), it is largely subjective in nature. Its presence is signified by feelings experienced by the task performer, most commonly difficulty (O'Donnell et al., 2005), uncertainty (Te'eni, 1989), and/or ambiguity (Oedzes et al., 2019). Of the three forms of task complexity, experienced complexity alone exists solely in the mind of the task performer. It can be viewed primarily as a function natural mental limitations vis-à-vis memory and processing capability, such as the long-known limits on short term memory capacity (e.g., Miller, 1956) and the mechanisms we have for overcoming these limits, such as chunking and the gradual process through which complex sequences of cognitive activities become automatic (Shiffrin & Dumais, 1981). Because a task's experienced complexity can range from negligible to impossibly hard—depending on the individual's familiarity and practice (e.g., the task of playing a piano sonata)—the experienced complexity of a task is best applied to a single task instance, fixed with respect to a particular performer and a particular point in time.

The level of experienced complexity can also exert a profound effect on the effectiveness of task performance. To achieve optimal performance, the cognitive demands of a task are best kept within a range above the levels that lead to boredom and below the levels resulting in information overload. The relationship between performance and cognitive demands has been described as the inverted U curve (Streufert & Streufert, 1978), signifying the sharp drop off when cognitive demands either fall below the desirable range or overload the performer's cognitive capacity. More recently, occupying this peak performance range has been referred to as achieving flow (Csikszentmihalyi et al., 2014), or being "in the zone" (Payne et al., 2011).

Because experienced complexity is influenced by naturally occurring human cognitive limits, the optimal range is unlikely to change dramatically over time. Nevertheless, as previously noted, repetitive practice of a task can reduce its demands. Alternatively, the individual may be able avoid uncomfortably high cognitive demands by transferring some or all parts of a task to other performers. These may be individuals or, potentially, constructed systems—most commonly IT-based.

Intrinsic complexity

The second type of complexity, *intrinsic complexity*, can be determined from the symbolic representation of the task, sometimes referred to as the problem space (Card et al., 1983). This form of task complexity bears some similarity to Wood's (1986) view of complexity and Campbell's objective complexity (1988) but differs in two important respects:

1. Being determined by the problem space used to perform the task rather than the task itself, intrinsic complexity may differ across task performers if they apply different problem spaces. For example, the intrinsic complexity of selecting elements of a stock portfolio may differ substantially if one performer uses a spreadsheet and another uses a Ouija board. (Naturally, one may choose to define the task such that the latter does not meet the criteria of the task rules).
2. By specifying that intrinsic complexity is based upon the symbolic representation of the problem space, it becomes possible to view it as extending across multiple performers, including non-human (e.g., IT-based) symbol manipulation systems. For example, Hærem et al. (2015) used North Sea counterterrorism to illustrate how the complexity of a task involving many human and non-human components might be modeled.

Because intrinsic complexity is determined by the underlying nature of the problem space, it can be treated as objective. There is, however, no clear consensus regarding whether task complexity should be viewed as a single value or as a collection of values. Campbell (1988) proposes four dimensions, Wood (1986) proposes three dimensions (but proposes that they can be added to form a "total complexity"). Hærem et al. (2015) reject the notion of different types of task complexity, arguing that they are really antecedents of a single underlying construct of task complexity, which they view as a function of the nodes and linkages within a task network. Whether or not a single underlying task complexity construct exists, we believe the consequences of intrinsic complexity (however it is operationalized) are likely to correlate with:

- The size of a computer program capable of fully simulating the problem space.
- The amount of time it would take to learn to perform the task according to the specified problem space.
- The size of a complete description of the problem space.

Another good indicator of intrinsic complexity is the amount of memory and computational power it takes to complete a task. In this regard, the game of chess would involve a problem space that is more intrinsically complex than the game of checkers. The evidence for this could include the fact that computers mastered checkers in the 60s but didn't master chess until the 90s. However, an unsophisticated problem space for playing chess might well prove to be smaller than the problem space needed to play master-level checkers. With respect to a task's scope, it is best defined with respect to the set of task instances that can be completed using the problem space for which it has been evaluated.

Under intrinsic complexity, the symbolic representation of the problem space can extend across performers. For example, a skilled U.S. tax accountant might complete a tax return using a set of rules (i.e., problem space) very similar to that incorporated in a tax preparation software application such as TurboTax (in theory, at least). If that were the case, the intrinsic complexity of the tax preparer working independently might be very similar to that of a novice using the software, since the novice's problem space includes access to all the rules embedded in the program.

Extrinsic complexity

Extrinsic complexity captures how the external environment responds to the task. It is the form of task complexity that is least addressed in the task complexity literature. We believe it to be important, however, since it incorporates an aspect of task complexity that goes largely unaddressed by that literature: the quality of task performance. Unlike experienced and intrinsic complexity, it best applied to a very broad set of task instances, as should become clear shortly.

The roots of extrinsic complexity are in complex systems theory, drawing heavily on concepts from evolutionary biology (e.g., Kauffman, 1993). The principal model used is that of a fitness landscape, which provides a functional mapping from the attributes of an entity (which might be a gene, an organism, an individual, an organization) to a fitness value. That value captures the likelihood that the entity will (a) survive, and (b) reproduce. In a low complexity landscape, the attributes of the entity contribute to the fitness value independently. For example, in a multiple-choice test, the attributes might correspond to the individual answers and the fitness might be the resulting test score. Assuming each attribute has a "right" value and is scored independently of the others, the landscape would have a single peak—where the correct answer is specified for every question.

In a high-complexity landscape, the attributes interact with each other to determine fitness; combinations rather than individual values are what matter. Whereas a low complexity landscape will have one optimum fitness point (i.e., a peak), a high complexity landscape will be rugged—i.e., will have many local peaks and sharp drop offs. A cookbook provides a good practical analogy for a rugged fitness landscape. Each recipe in the book could be assigned a fitness value. In this example, fitness would be a predictor of the likelihood that you would be willing to make the recipe again after trying it (i.e., survival) or even copy it to give to a friend (i.e., reproduction). What makes this landscape rugged is that each recipe represents a local fitness peak in the authors' minds. Otherwise, they would write in those incremental changes (e.g., adding a bit more sugar than the original recipe calls for) needed to make it a peak. Thus, the landscape for the cooking task within that one book could consist of (literally) thousands of local peaks (recipes), with countless more peaks across the entire cooking landscape.

The cooking example also illustrates a variety of general complex landscape properties:

- Individual attributes mainly contribute to fitness in combination with other attributes, e.g., the presence of garlic adds to the fitness of some recipes and detracts from others.
- Seemingly insignificant changes to attributes can have a big impact on fitness, e.g., consider what happens when baking powder (the rising agent) is inadvertently left out of a cake recipe.
- Local peaks can exhibit very high levels of variation, e.g., some recipes are very popular while others will barely ever be used.
- Even with an understanding of the mechanisms driving fitness, the fitness of a new, untried combination is nearly impossible to predict without testing it. For example, when IBM used Watson to develop new recipes the results were far from uniformly successful (Pinel, 2015).

Although the fitness landscape concept has been applied to some business tasks, such as strategy formulation (e.g., Levinthal, 1997), it has not been incorporated into prevailing task complexity models. In adapting the fitness landscape concept to task complexity, we can conceive of each task end state (which includes information on how the task was performed) as having a fitness value. If the value is low, we would avoid using that approach in the future. We would also try to avoid contexts where we were forced to use that same approach. Where fitness is high, we would likely use the same approach should a similar task instance ever come up (i.e., the approach would survive). Moreover, other performers watching us may seek to imitate the approach (i.e., reproduction). Because we would expect performance quality to elicit similar reactions, the values of outcome quality and fitness might logically serve as proxies for each other.

Complex landscapes are generally associated with complex systems (such as ecologies). While the underlying factors that lead to complex systems behavior remain the subject of study, three general characteristics are commonly associated with increasing complexity (Gill & Mullarkey, 2017):

- Increase in the number of elements in the system.
- Increase in the number and density of interactions between elements in the systems.
- Increase in the rate at which interactions between elements affect each other.

As landscape complexity grows, we would expect to see the following changes in the landscape's characteristics (Gill & Mullarkey, 2017):

- Increased number of local fitness peaks: Although there can be many positions on the simplest fitness landscape, there are very few peaks and those peaks are relatively easy to find through incremental search. More peaks mean sharper rises and drop-offs and more potential alternatives to choose between. A landscape with many peaks also increases the risk of ending up on a low fitness peak if incremental search is used.
- Reduced ability to determine meaningful causality: In an environment with low extrinsic complexity, main effects dominate interactions, so it is meaningful to impute causality to specific attributes. As extrinsic complexity increases, it becomes nearly impossible to decompose attributes that contribute to fitness; experimentation or observation of experiments becomes the only way to assess fitness.
- Distributions of fitness become increasingly non-normal: Where fitness is determined by the sum of fitness contributions of individual attributes, fitness values across the landscape are likely to follow a normal distribution. In landscapes of increasing complexity, non-normal

distributions (particularly those governed by the power law) abound. In the book *The Black Swan*, Nassim Nicholas Taleb (2007) gives a hypothetical example of height following a power law, wherein it would be possible to see individuals whose heights exceed the heights of another thousand individuals combined. Wealth, a plausible proxy for economic fitness, is an example of a value that follows a power law in the real world. For example, the top 1% of U.S. earners are wealthier than the entire middle class combined (Kaplan & Kiersz, 2021). This would be impossible if wealth followed a normal distribution.

- Punctuated Equilibrium: Extrinsically complex landscapes lend themselves to punctuated equilibrium. This concept was devised by Stephen Jay Gould (Gould & Eldredge, 1972) and entails extended periods of homeostasis followed from time to time by large events that change the entire landscape.

These characteristics make it much more difficult, confusing, and frustrating to navigate an extrinsically complex landscape. While the multitude of peaks can provide huge opportunities, these opportunities are not uniformly distributed. Fitness power laws raise the stakes (compared with normal distributions), as the most successful will occupy a position of fitness that may be one hundred, one thousand, or ten thousand times better than a mediocre position. Extrinsic complexity also adds an element of ambiguity to the results of one's decisions or efforts. Being more difficult to assess causality, it is hard to predict the effect that a decision is going to have on one's fitness overall. The larger number of fitness peaks also has the potential of overwhelming people by presenting them with too many options to choose from.

Summary

The three forms of complexity are summarized in Table 1.

Table 1: The Three Forms of Task Complexity

	Experienced Complexity	**Intrinsic Complexity**	**Extrinsic Complexity**
Definition	Complexity experienced based on the cognitive load brought about by a task	Complexity in the symbolic representation of a task (rules and alternatives, processing power, etc.)	Complexity of the landscape of task outcomes vis-à-vis interrelatedness of elements, number of fitness peaks, turbulence of the landscape.
Result of increase	Perceived difficulty, uncertainty, ambiguity	Larger problem space, number of branches, time to learn	Fitness landscape ruggedness, punctuated equilibrium, power laws
Scope of initial and target state sets	Very narrow	Sharing the same problem space	Very broad
Effect of repeated task performance	Decreases	Increases	Indeterminant

Complexity in Information Systems

The topic of complexity has been researched frequently in the management and IS fields. In this research, complexity is generally categorized as either the complexity of tasks (Campbell, 1988; Wood, 1986), or the complexity of systems (Beese et al., 2016; Liang et al., 2015). Previous research has also studied the interaction between task complexity and system complexity wherein a co-dependency arises between a task and a system. The user is dependent on the system to complete the task and the system is dependent on the user's knowledge of the system's semantic relationship with the task. From this co-dependency, representational complexity emerges, presenting an obstacle to effective use of a system (Lauterbach et al., 2020). As it relates to our framework, representational complexity is the intrinsic complexity leftover after users have offloaded some of the intrinsic complexity of a task to a system. The experienced complexity of an individual using the system will decrease as the user becomes accustomed to it.

There has been a recent call for more IS research on digital solutions to the problems brought about by the complexity of digital systems (Benbya et al., 2020). Sociotechnical systems and the complexity thereof result in "wicked" problems that can be tamed but not solved completely (Tanriverdi et al., 2010). Complexity oriented methods have been applied to such wicked problems as Recommender systems (Malgonde et al., 2020).

Incremental changes in digitized processes can bring about bursts of complexity and large changes in structure (Pentland et al., 2020). Research has been conducted as to how to use digital technologies to steer organizations through phase changes from old states to desired new states (Sandberg et al., 2020). Also studied in the IS literature is organizational complexity, or a non-linear interaction between elements in an organization resulting in emergent effects (Park & Mithas, 2020). When causality is difficult to define and causal elements are intertwined, Qualitative Comparative Analysis can be used to glean insights and make predictions without assuming that causal factors are decomposable (Iannacci et al., 2022).

THE PROPOSED THEORY

The use of IT in task performance can potentially impact all three forms of task complexity. We further propose that these three forms of complexity, when enabled by IT, can interact to establish what we call a complexity cycle. This cycle, illustrated in Figure 1, begins when—for whatever reason—the experienced complexity associated with performing task instances (along with anything else happening in parallel) moves performers towards the excessive demand side of the previously mentioned inverted U curve. The performers then have a variety of options to move to a more comfortable level of experienced complexity. These include:

- Practicing the task until it becomes routine.
- Taking shortcuts (e.g., imitating other task performers) to reduce the cognitive demands of the task.
- Finding other performers to share the task with.
- Using IT to offload all or part of the task with performers.

If the last of these options is selected, the intrinsic complexity of the task will likely increase. For example, when individuals employ tax preparation software to complete their income taxes, the software not only performs necessary computations—which would not have much impact on intrinsic complexity—it also provides them with access to a vastly expanded problem space relating to the tax code. While an individual task performer's decision to switch to tax software is not likely to have much impact on the tax preparation fitness landscape, if many performers make this switch, we are likely to see such software evolve quickly, and many new variations emerge. Moreover, if the use of the software becomes widespread, it could impact the agency responsible for collecting taxes and updating the tax code. The increased flexibility provided by the new systems could then embolden legislators to pass more complicated tax laws, leading to increased intrinsic complexity of the tax preparation task. Furthermore, individual task performers may be impacted by extrinsic complexity increases driven by forces outside of the tax preparation task. For example, the introduction of new asset classes (e.g., bitcoin) may demand changes to the system of tax laws. Because the fitness landscape for one entity co-evolves with fitness landscapes for other entities (Kauffman, 1993), IT-enabled extrinsic complexity from one task landscape can transform other task landscapes. As a result, the behaviors that are associated with complex landscapes (e.g., ruggedness, indeterminant causality, power law outcomes, punctuated equilibrium) can bleed across landscapes. The increasingly turbulent behaviors of the task environment will cause performers to seek out additional help in reducing experienced complexity. If done through use of IT, the cycle continues.

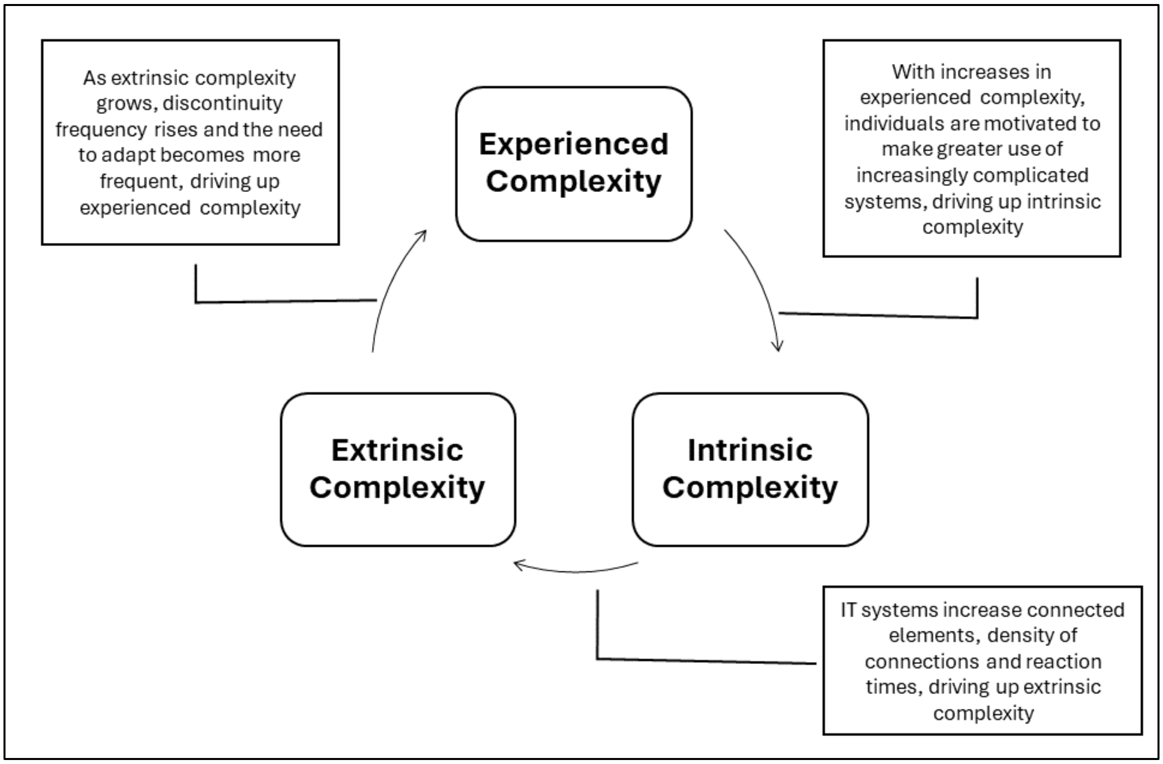

Figure 1: The IT-driven complexity cycle

APPLICATION OF THE THEORY: CHATGPT AND OTHER EXAMPLES

In this section, we briefly explore how the Complexity Cycle might be used to identify potential unintended consequences of widespread adoption of emerging technologies. We begin by looking at ChatGPT, then briefly consider blockchain and quantum computing.

CHATGPT

A recent example that illustrates the how the complexity cycle may be applied can be found in the recent (December 2022) public release of OpenAI's advanced chatbot: ChatGPT. The application employs advanced language modeling based on user prompts and a large language model and exemplifies many of the capabilities of generative AI. The tool uses reinforcement learning from human feedback, wherein the actions taken by ChatGPT in the form of language output are rated by users, allowing the platform to learn from every attempt to respond to a prompt (Ramponi, 2022).

ChatGPT has been applied to accomplish a variety of tasks such as college essay writing (Mitchell, 2022), medical writing (Biswas, 2023), and journalistic writing (Longoni et al., 2022). It can explain complex concepts and has even managed to pass a Wharton MBA exam (Rosenblatt, 2023).

Looking at the tool from a task perspective, consider the example of ChatGPT's success at essay writing through the lens of the complexity cycle. At a university in South Carolina, a student submitted a 500-word essay on David Hume's paradox of horror (Mitchell, 2022). The essay was of such a quality that the professor was unable to prove that it was not the student's own writing, except by goading the student into confessing. It is worth noting that the decision to use ChatGPT to write this essay on Hume represents a decrease in experienced complexity, but an *increase* in intrinsic complexity—both drastic. Experienced complexity is decreased because the student no longer had to craft a 500-word essay on Hume, but rather a one to two sentence prompt to feed ChatGPT. Intrinsic complexity increased since the problem space of the task grew given that it was drawing upon the entire base of knowledge contained in ChatGPT.

Just as the problem space of the essay writing task was increased, the problem space of many other tasks has been increased by way of the offloading of these tasks to ChatGPT. By early February of 2023, ChatGPT was well on its way to surpassing 100 million users (Garfinkle, 2023). Stated another way, that corresponds to 100 million users all employing essentially the same problem space for a wide variety of tasks. We might then speculate that if millions of individuals addressing a similar problem all come up with similar solutions (by virtue of using the same problem space) much more rapidly than in the past, the fitness of these solutions is bound to be impacted—leading to a rapidly changing fitness landscape. This would translate to an increase in extrinsic complexity facing the performers. Closing the loop, we might further speculate that the increasingly dynamic fitness landscape driven by generative AI would, in turn, lead to increases in experienced complexity. These increases would, in turn, motivate further offloading of task activities to AI tools. And so, the cycle would continue.

Blockchain

While exploring the mechanics of blockchain technology is beyond the scope of our paper, the key feature of blockchain is to provide a means of recording transactions that:

- Cannot be altered once a transaction is recorded
- Can be audited
- Can be conditioned on the completion of other transactions.

Collectively, these three capabilities represent activities that would often require an intermediary, such as a lawyer or agent. In consequence, a key systemic change expected to occur with blockchain's increasing adoption is widespread disintermediation (e.g., Srikanth, 2017).

Viewed in terms of the extrinsic complexity of the environment, widespread disintermediation might be expected to exert a significant impact. In the current environment, intermediaries play an important role in controlling the speed and frequency of transactions. For example, intermediaries can determine the speed at which funds are transferred between accounts or the timing of a real estate closing. Once disintermediated, these transactions could occur much faster and at lower cost—encouraging a greater frequency of smaller transactions. Both of these systemic changes would typically increase the extrinsic complexity of the environment according to our model.

With increasing extrinsic complexity, individuals participating in the system—particularly those operating as intermediaries or depending on intermediaries--would experience increasing cognitive demands. In response, they would be motivated to implement additional blockchain and other technologies, driving further increases in extrinsic complexity, and so forth.

Quantum Computing

Quantum computing refers to a class of computing technologies that employ principles of quantum mechanics, such as superposition and entanglement. Reliance on these principles cause it to differ radically in architecture and capabilities from today's ubiquitous digital technologies. For this reason, quantum technologies are expected to offer huge advantages for certain types of computing problems, while providing little or no benefit for others (Inglesant et al., 2021).

Because quantum phenomena include the ability to occupy many states simultaneously, the technology is expected to revolutionize tasks that can benefit from pursuing multiple threads simultaneously. Examples of such tasks include encryption, optimization, and simulation. Quantum computers may also support certain problems that are "beyond the capability of any classical computer" (Inglesant et al., 2021, p. 1368).

The practical applications of quantum computing remain uncertain at the present time. Its radical architecture and anticipated capabilities suggest, however, that its impact on the global economic environment could be transformative. For example, quantum computing has the potential to render existing encryption algorithms ineffective (Inglesant et al., 2021). Should this happen, virtually every information system where privacy or security is important would need to be redesigned. We speculate that such a development could lead to a discontinuity in our technology environment unparalleled in digital history.

In our two earlier examples, ChatGPT and blockchain, we described a process whereby increasing use of technologies gradually causes the extrinsic complexity of the economic and technology environment to grow. Such growth would be expected to increase characteristic complex system behaviors, such as punctuated equilibrium. Quantum computing, in contrast, illustrates a potential scenario whereby the technologies themselves precipitate a massive discontinuity in the economic environment. In all three examples, however, human participants in the system would be expected to react by relying more heavily on technologies to reduce their experienced complexity. And the cycle continues.

UNINTENDED CONSEQUENCES OF COMPLEXITY CYCLE

Information technology has yielded many benefits to society at large. These include increased productivity, greater ease of access to information, a wider variety of opportunities for recreation, and enhanced capabilities for social interaction. Nevertheless, the complexity cycle model posits that these may come with long-term hidden costs. For our purposes, it is useful to distinguish between the costs that are:

- directly related to the individual performers
- likely to impact the performance of the task, and
- more systemic in nature and are expected to occur only with the widespread deployment of the technologies in question.

INDIVIDUAL PERFORMER RISKS

Deskilling: When IT is used to reduce the experienced complexity associated with a task, the skills that are transferred are likely to atrophy. In the era of intelligent systems, more and more decision-making elements of the task are likely to be transferred, often using data analytics and artificial intelligence as a replacement for domain expertise (Sambasivan & Veeraraghavan, 2022). That will leave performers with a reduced skill set and, most likely, reduced adaptability to future task changes.

Barriers to advancement: Increasing reliance on IT in performing tasks can potentially create barriers to further advancement in an organization in two ways. The first is a direct consequence of deskilling, which can increase the gap between what the individual learns on the job and what needs to be known to move to the next organizational level. The second is that jobs will be redesigned to demand technical skills, such as the ability to use AI effectively, that existing intermediate-level workers may not possess (Shiohira, 2021, p. 14).

Task-Specific Risks

Perpetuation of Past Practices: As IT is applied to more intrinsically complex tasks, the ability of developers and task performers to articulate the rules governing system behavior is impaired. Machine learning and other AI techniques address this problem by inferring relationships from past data. Historical bias and population bias, for example, can both lead to discriminatory results when data is used to train machine learning systems (Mehrabi et al., 2021). These relationships are often not in the form of understandable rules but are instead embedded in opaque statistical relationships and coefficient weights. If such data incorporated biases from past decision-makers, such biases will likely be perpetuated undetected.

Systemic Risks

The co-evolution of landscapes means that even if a task doesn't experience the risks just described, it may still be impacted by the growing extrinsic complexity of its environment. Examples include the following.

Erosion of Explainable Causality: What constitutes causality remains a topic of debate, even within the IS field (Markus & Rowe, 2018). It is commonly framed as a one-way relationship between a set of factors (the cause) and a set of outcomes (the effect). While causality seems likely to exist regardless of the extrinsic complexity of the system in which a phenomenon is observed, our ability to articulate that causality is likely to decline as its complexity grows. For example, what causes one recipe to "taste better" than another?

The interconnectedness and interactions between elements that characterize extrinsic complexity make it very difficult to predict the ceteris paribus effect of an incremental change to a task on its overall fitness. Owing to the high level of interaction between attributes as complexity grows, simple statistical tools such as linear regression fail when observed data is drawn from a rugged landscape (Gill, 2012). Individuals operating on such landscapes will also find that the fitness associated with untested combinations is nearly impossible to predict.

Shortened Time Horizons: The interconnectedness enabled by IT can cause changes in one part of the task environment to ripple through all parts of the task environment and bleed into other task environments. Responses to changes from systems and agents tend to become much faster as information is exchanged in nanoseconds. This can shorten the periods of homeostasis between system changing events characterized by punctuated equilibrium. In addition, since its very inception, IT has been able to process quantitative data faster and more accurately than humans. Unfortunately, we could find no research that specifically addressed the impact IT use on individual time horizons. This absence may not be surprising, as even futurists have trouble clarifying the concept (e.g., Brier, 2005). That research does point out, however, that complexity has a significant impact on how far ahead we can visualize (p. 844). It follows that as IT increases the rate at which changes can proliferate though an environment, the time frame over which we can comfortably envision the consequences of our actions will shorten.

Owing to the punctuated equilibrium behavior observed in many extrinsically complex systems, including business environments (Gersick, 1991), we can also predict that increasing extrinsic complexity could lead towards short-term bias. The rationale is as follows. Discontinuities are perceived as being unpredictable, both in timing and effect (Taleb, 2007). We would expect analysis of the short-term future (i.e., before the environment experiences a major transition) to be more effective at reducing uncertainty than analysis of the long term (given the unpredictability of discontinuities). We would therefore expect that increasingly relying on IT to analyze decisions (as a means of controlling experienced complexity) would make us more confident of our analysis of short-term solutions compared to long term solutions. Since decision theory assumes that the level of uncertainty is negatively factored into our choices, applying an approach that reduces the uncertainty of the short-term options while having minimal impact on longer term options would be expected to drive our preference towards the more certain (short term) choices, all other things being equal.

Inequality: The direct implications of IT on inequality—through differentials in access and differentials in skills—have long been discussed (Hargittai et al., 2019). The increasing use of IT in tasks and the resultant incorporation of tech elements into these systems certainly would tend to exacerbate this form of inequality. Furthermore, although deskilling directly impacts task performers, reducing their potential economic value in the long run, it also supports the creation of a parallel (and likely much smaller) set of task performers—the creators of the technologies used to support the task. That set of individuals must necessarily become more and more skilled as they take on tasks demanding problem spaces of ever-increasing intrinsic complexity.

The potential consequences for inequality of IT's impact on the extrinsic complexity of the environment is less recognized. There is considerable empirical evidence that extrinsically complex systems produce non-normal distributions of outcomes, frequently in the form of power laws (e.g., Taleb, 2007). The result: highly visible inequality. While this effect has not been directly addressed, a self-reinforcing cycle leading to inequality driven by IT (Ragnedda et al., 2022) and inequality driven by structural changes that were enabled by IT (Bauer, 2016), such as complex supply chains, have been proposed. Both these proposed effects would be consistent with growing extrinsic complexity.

Tribalism: The use of IT is not the only way to reduce experienced complexity. In an extrinsically complex environment, we have already noted that causality is very hard to determine, so analysis may well fail in the search for fitness. An alternative is to seek out individuals or practices that appear to be high-fitness and imitate them as closely as possible. In fact, simulations suggest that such imitation may be an excellent approach to achieving high fitness as extrinsic complexity grows (Gill, 2012). In highly rugged landscapes, however, even small differences in attributes can have a large impact on fitness (Gill & Mullarkey, 2017). It can therefore benefit the individual to seek out other individuals who are as similar as possible across relevant attributes. By observing how the landscape rewards and punishes the behaviors of these self-similar individuals, it becomes possible for the decision-maker to avoid the risk of engaging in behaviors that could result in serious fitness declines. Moreover, as landscapes become more extrinsically complex, the risk of large fitness declines accompanying small changes grows. The logical consequence of dealing with such landscapes is for self-similar individuals to form into groups, an outcome referred to as homophily (Gill, 2012). For such a group to be effective in overcoming ruggedness, all members would need to share a common set of core attributes (e.g., personal characteristics, opinions, values) that define the group while allowing variation in non-core attributes as a means of testing other combinations for fitness. Individuals could be members of several of these groups, but the core attributes would necessarily be different across groups. For example, the core attributes for a group of individuals based around performing the same task might be quite different from the attributes associated with membership of a weekly book club.

In addition to increasing the ruggedness of the landscape—thereby *motivating* the formation of these groups—IT also helps to *enable* their formation and ongoing activities. The second stage of the internet era, sometimes referred to as Internet 2.0, included the formation of social networks, making it easier to:

- Form homophilic groups untethered by geography.
- Share experiences with other group members.
- Reinforce activities that support group identity and castigate those that are inconsistent with the group's defining core attributes.

A potential consequence of these networks—perhaps unintended, perhaps not—is the formation of echo chambers (Kitchens et al., 2020). In these environments, expressions of support for core attributes are naturally encouraged. Variations across non-core attributes will similarly be encouraged, since they provide evidence for the fitness or non-fitness of untested combinations that will likely be relevant to the rest of the group. The underlying structure of rugged fitness landscapes also suggests that with growing extrinsic complexity, members of dissimilar groups will become increasingly resistant to compromise. On a rugged landscape, the area between two adjacent peaks is necessarily a low fitness valley. This can lead to an underlying hostility between groups that can best be described as tribalism, a term that has been used to describe the subreddit communities on the reddit platform (Robards, 2018). Unfortunately, the very erosion of causality that accompanies increased extrinsic complexity makes it unlikely that logical arguments or appeals to causality will have much effect in swaying opinions.

IMPLICATIONS FOR INFORMING SCIENCE

The proposed complexity cycle (and the associated specific/systemic) risks could have significant implications for how we can inform effectively—the core of informing science:

> The fields that comprise the discipline of *Informing Science* provide their clientele with information in a form, format, and schedule that maximizes its effectiveness. (Cohen, 1999, p. 215).

In this section we first consider the informing challenge presented by the proposed complexity cycle and then consider the paradoxical problem of trying to address that challenge using IT.

THE INFORMING CHALLENGE OF COMPLEXITY

The study of complexity and its impact on informing has been a recurring theme in the informing science transdiscipline. For example, a single client resonance model, shown in Figure 2, has been proposed to illustrate the challenges of ensuring that a client accurately receives and internalizes a sender's message. Rather than being thought of as a theory, it is best viewed as a conceptual scheme (Gill, 2011) for thinking about how messages are internalized by a client. Of particular importance, rather than assuming that a sender's messages are faithfully received, it highlights the potential for communications to fail owing to lack of attention, distortion/interference, and outright rejection.

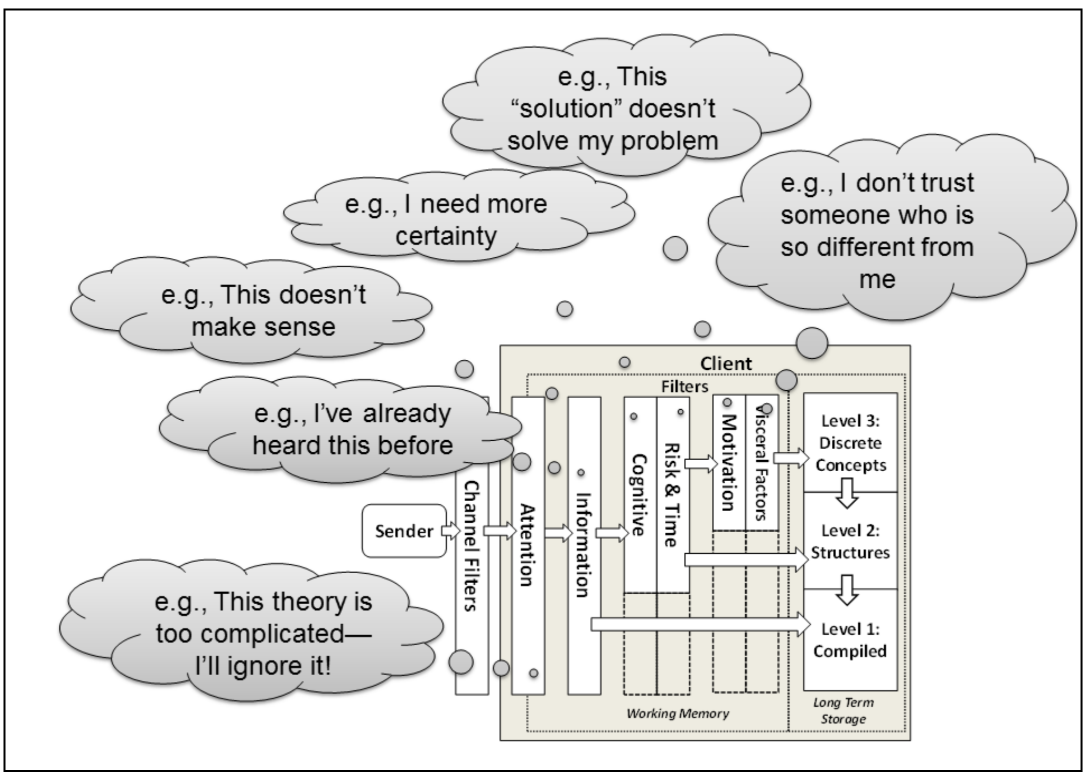

Figure 2: Single Client Resonance Model (Gill, 2015, p. 268)

The *attention filter* is used to describe situations when clients ignore messages sent to them. Attention may be withheld either intentionally (e.g., by focusing attention elsewhere) or unintentionally (e.g., by not attending to the channel used to send the message). It can serve to reduce experienced complexity by limiting the client's information processing load.

The potential role that increasing IT-driven complexity can play with respect to attention should be self-evident. IT has enabled numerous channels that could not have otherwise existed: email, text, social networks, communication apps, etc. The result is not only more channels than we can attend, but also more content than we can possibly absorb. Deskilling may also prevent clients from attending to messages that they perceive to fall outside of their domain of understanding.

The *information, cognitive and risk/time filters* can subject messages to distortion or interference as well as preventing messages from being absorbed. The challenge here is that incoming messages do not exist in a vacuum. Instead, they are interpreted subject to what we already know or believe. The information filter screens out information that we perceive that we already know—whether that is the case or not—and limits the rate of information transfer. The cognitive filters assess the consistency of the message with our existing beliefs, in some cases distorting it to achieve greater consistency or blocking it altogether. Not only do these filters potentially impact experienced complexity through reducing the amount of information being processed, they can also reduce the difficulty, uncertainty and ambiguity that can stem from conflicting information.

With respect to the impact of systemic risks, the erosion of explainable causality makes it harder to present simple explanations. That, in turn, is likely to make pre-existing knowledge harder to disrupt (the cognitive filter) and to make it more likely that we will treat an incoming message as something we already know (the information filter). A similar argument can be made for the effect of perpetuation of past practices. Shorter time horizons, resulting from increasing extrinsic complexity, are likely to encourage us to focus mainly on the immediate consequences of a message. Long-term implications are therefore more likely to be ignored.

The *motivation/visceral factors filters* can lead to rejection of messages regardless of their veracity. If we do not trust the source of the message, or if accepting a message as true might threaten our position in the community, we will tend to reject it. A similar rejection is likely if a message generates negative emotions. By the same token, a client may be motivated to suspend critical judgment of a message from a trusted source or one consisting of content that the client wants to hear.

The most obvious systemic risk for these filters is tribalism, which is built around a common set of shared core beliefs. Polarization of political beliefs could be used as an example of this phenomenon. In a world of high extrinsic complexity, assessing the veracity of a message through logical analysis may be impossible (i.e., erosion of explainable causality). In such cases, reinforcing tribal membership though achieving consistency with core beliefs may be the operative motivation in accepting or rejecting a message.

The Paradox of Addressing Complexity's Informing Challenges

We do not foresee any all-purpose solution to addressing complexity's informing challenges. Nevertheless, if we choose to attack the challenges directly, it is relatively easy to propose potential approaches—nearly all of which involve information technology. For example:

- AI systems could be constructed that attend all channels and provide clients with all information that they perceive would be relevant to the client. Such curation systems could work collaboratively with the attention filter.
- Creating multi-sensory channels that take advantage of our ability to absorb content more rapidly when presented simultaneously in multiple formats. These channels can potentially increase the effective capacity of the information filter.

- New channels could be devised that are specifically constructed to limit the potential information content of messages, making them more easily absorbed and more immediate. This would reduce the load on the cognitive and risk/time filters.
- AI-enabled aggregator systems could be constructed that provide the client with only content that is unlikely to be rejected or distorted. This would limit the demands on the motivation and visceral filters.

Unfortunately, these approaches (and many others that we could propose) are not novel. Indeed, every one of them is already in place or advancing rapidly (e.g., ChatGPT, the Metaverse, Tik Tok, Flipboard). More to the point, however, widespread adoption of fixes such as these will ultimately serve to increase the overall extrinsic complexity of our environment for the reasons previously described. We would then expect experienced complexity to rise, creating a need for new solutions. And the complexity cycle persists…

The other approach to addressing the negative consequences of the complexity cycle would be to abandon or drastically limit the use and evolution of IT. We have already seen efforts along these lines with respect to AI (Levin & Downes, 2023). Our own view, however, is that nothing short of complete societal collapse—as occurred with the advent of the Dark Ages in Europe—will put the IT genie back in the bottle.

Fortunately, we believe that addressing the effects of the complexity cycle does not require us to become a Luddite. Our view is that the greatest danger presented by over-reliance on IT is that we—as a society—loose the capacity to process information without IT. We can already see some examples of this. Just ask typical young adults to perform two-digit multiplications in their head or read a paragraph written in cursive. From a practical standpoint, these skills are nearly useless in a world where IT is ubiquitous. Nevertheless, we see them as being representative of a class of cognitive skills that, as a society, we should be concerned about losing.

Rather than attempting to disable the complexity cycle—assuming that would be even remotely possible—our recommendation would be twofold:

1. Recognize the cycle's potential effects and treat them as an externality—the term economists use to describe broader negative impacts of locally beneficial activities.
2. Build activities into our education system and everyday life that develop and maintain cognitive capacities that are likely to atrophy through overuse of IT.

Economists have already considered a variety of remedies for the first of these—typically a mix of regulation and taxation. These have become increasingly challenging to implement in a global context. For example, what happens if one super-power regulates the development of AI while another allows it to run free? Despite these practical obstacles, the first step will necessarily be to recognize that a problem does exist.

To implement the second of these recommendations would require us to reconsider current trends, many of which seem to be going in the opposite direction. Activities that served to develop cognitive skills that traditionally do not rely on IT—such as the arts, music, and languages—have been de-emphasized in K-12 curricula (e.g., Commission of the Arts, 2021; Commission on Language Learning, 2017). In higher education, enrollments in the humanities are dropping (Pergola, 2014; Townsend & Bradburn, 2022). Moreover, the humanities departments that remain have become increasingly uniform in their politics (Magness & Waugh, 2022/2023), presenting a significant visceral barrier to participation by individuals outside of the tribe.

Reversing these trends would not be easy. The motivation filter could present a significant barrier, since the *relative* short-term advantages that these cognitive skills confer have likely declined owing to technological advancements, such as mathematical equation solvers, computer generated artwork, recorded music, generative AI, and automated translators. To prevent further atrophying of such skills, a compelling case needs to be established for their benefits to the individual in an increasingly automated world. Such a case will need to be made through rigorous research—emotional appeals are likely to fall short. Unfortunately, anecdotal arguments coming from older individuals who already acquired such skills in a world where IT was not ubiquitous are unlikely to be persuasive to Millennial and Z-generations that grew up relying on technology and connectivity.

LIMITATIONS

We have referred to the complexity cycle as a theory based on the widespread acceptance of the term "theory". Convenience aside, we might have better described it as a conceptual scheme (Gill, 2011) for a couple of reasons:

DUBIOUS FALSIFIABILITY

First, given the nature of the complexity cycle and the general difficulty of establishing meaningful causality in complex systems, we are not sure how it could be tested rigorously. Having said this, it would certainly be possible to design investigations that could lead to results consistent or inconsistent with the complexity cycle's predictions. For example:

- Interpretive of individual tasks and performers studies could assess the degree to which adoption of supporting technologies (a) was motivated or partially motivated by performers experiencing high cognitive loads, and (b) if these options were initially successful in bringing cognitive demands to acceptable levels. The proposed theory would predict both (a) and (b) to be the case, but that, over time, increases in the extrinsic complexity of the broader environment would necessitate further IT adoption.
- Longitudinal studies could be conducted that examine the behaviors of industry environments before and after the widespread adoption of a technology. The proposed theory would predict that indicators of system complexity (e.g., frequency and size of discontinuities, emergence of power law distributions of participant performance, increasing diversity in successful participants/business models) would increase.

Unfortunately, these types of studies—particularly the latter—would be prone to demonstrating correlation rather than proving causality. We certainly would *not* assert that the complexity cycle is the sole force involved when a technology is implemented. As such, excuses could always be found not to reject the theory upon encountering inconsistent results. As Popper (1963) suggested, an unfalsifiable theory is not scientific.

SENSEMAKING

Second, one of the most valuable uses of a conceptual scheme is to provide a means of sense-making (Gill, 2011). We believe that the three forms of task complexity and their cyclical relationship provide a useful way of framing IT's impact on tasks and the broader environment. As is the case for conceptual schemes in general, it is up to the individual to assess whether it seems applicable (and useful) in a particular situation.

We further note that despite this paper's focus on the dark side of IT, our view of technology is nowhere near as grim as the paper would suggest. Nor would we recommend draconian measures to inhibit future IT implementation. We simply seek to build awareness of possible negative consequences. For future research, our greatest concern with the conceptual scheme is its vacillation between task-specific effects (which are relatively easy to detect and illustrate) and broader system effects, which are interesting but not necessarily intuitive or testable. More thoroughly researched examples are needed to better illustrate the relationships we propose, as well as counterexamples to establish their limits.

Conclusions

This paper's goal has been to propose a relationship between the use of IT to address task complexity and widely observed unintended negative consequences. By increasing our reliance on technology, we change tasks in positive ways, but open ourselves up to unintended and undesired side-effects at the task and broader environment levels. As regards task-level effects—such as deskilling and perpetuation of undesirable past practices—we believe that recognizing the danger and employing thoughtful task redesign can go a long way towards reducing the damage.

The more speculative element of the paper is the role IT may play in making co-evolving environments more extrinsically complex. We acknowledge that for this phenomenon, remediation is more difficult. It would be a fool's errand to try to halt the use of all IT that could increase extrinsic complexity. IT provides far too many direct benefits. We instead believe that extrinsic complexity should be treated as a negative externality of the creation and modification of information technologies and systems. Unfortunately, externalities are always difficult to deal with and the most readily available cures (e.g., taxing the behavior or regulating it) are often worse than the disease. If we decide that IT-enabled complexity must be contained, we must be careful lest the measures we put in place to combat complexity end up making the task environment even more complex.

References

Aanestad, J., Kankanhalli, A., Maruping, L., Pang, M.-S., & Ram, S. (2021). Special Issue—Call for Papers—Digital Technologies and Social Justice. *MIS Quarterly*. pp. 1-9. https://misq.umn.edu/pub/skin/frontend/default/misq/pdf/CurrentCalls/SI_DigitalTechnologies.pdf

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market?. *The Quarterly journal of economics*, *113*(4), 1169-1213. https://doi.org/10.1162/003355398555874

Bauer, J. M. (2016, July 23). Inequality in the information society. *Quello Center Working Paper* https://doi.org/10.2139/ssrn.2813671

Bawden, D., & Robinson, L. (2009). The dark side of information: Overload, anxiety and other paradoxes and pathologies. *Journal of Information Science*, *35*(2), 180-191. https://doi.org/10.1177/0165551508095781

Beese, J., Aier, S., Haki, K., & Aleatrati Khosroshahi, P. (2016). Drivers and effects of information systems architecture complexity: a mixed-methods study. *Proceedings of 24th European Conference on Information Systems (ECIS) 2016*. https://www.alexandria.unisg.ch/entities/publication/216dc199-38fe-4206-9d92-28fd61e27ed4/details

Benbya, H., Nan, N., Tanriverdi, H., & Yoo, Y. (2020). Complexity and information systems research in the emerging digital world. *Mis Quarterly*, *44*(1), 1-17.

Biswas, S. (2023). ChatGPT and the Future of Medical Writing. *Radiology*, *307*(2). https://doi.org/10.1148/radiol.223312

Braverman, H. (1998). *Labor and monopoly capital: The degradation of work in the twentieth century*. NYU Press.

Brier, D. J. (2005). Marking the future: A review of time horizons. *Futures, 37(8)*, pp.833-848. https://doi.org/10.1016/j.futures.2005.01.005

Campbell, D. J. (1988). Task complexity: A review and analysis. *Academy of Management Review*, *13*(1), 40-52. https://doi.org/10.2307/258353

Card, S. K., Moran, T. P., & Newell, A. (1983). *The psychology of human-computer interaction*. Earlbaum.

Clarke, R. (2016). Big data, big risks. *Information Systems Journal*, *26*(1), 77-90. https://doi.org/10.1111/isj.12088

Cohen, E. (1999). Reconceptualizing information systems as a field of the transdiscipline informing science: From ugly duckling to swan. *Journal of Computing and Information Technology, 7*(3), 213-219.

Commission of the Arts. (2021). *Art for life's sake: The case for arts education*. American Academy of Arts & Sciences. https://www.amacad.org/sites/default/files/publication/downloads/2021-Art-for-Lifes-Sake.pdf

Commission on Language Learning. (2017). *America's languages: Investing in language education for the 21st century*. American Academy of Arts & Sciences. https://www.amacad.org/sites/default/files/publication/downloads/Commission-on-Language-Learning_Americas-Languages.pdf

Csikszentmihalyi, M., Abuhamdeh, S., & Nakamura, J. (2014). Flow. In M. Csikszentmihalyi, *Flow and the foundations of positive psychology* (pp. 227-238). Springer, Dordrecht. https://doi.org/10.1007/978-94-017-9088-8_15

Faik, I., Barrett, M., & Oborn, E. (2020). How information technology matters in societal change: An affordance-based institutional logics perspective. *MIS Quarterly*, *44*(3), 1359-1390. https://doi.org/10.25300/MISQ/2020/14193

Fotheringham, M. J., Wonnacott, R. L., & Owen, N. (2000). Computer use and physical inactivity in young adults: Public health perils and potentials of new information technologies. *Annals of Behavioral Medicine*, *22*(4), 269-275. https://doi.org/10.1007/BF02895662

Garfinkle, A. (2023). ChatGPT on track to surpass 100 million users faster than TikTok or Instagram: UBS. *Yahoo*. https://news.yahoo.com/chatgpt-on-track-to-surpass-100-million-users-faster-than-tiktok-or-instagram-ubs-214423357.html

Gersick, C. J. (1991). Revolutionary change theories: A multilevel exploration of the punctuated equilibrium paradigm. *Academy of management review, 16*(1), 10-36. https://doi.org/10.5465/amr.1991.4278988

Gill, T. G. (2011). When what is useful is not necessarily true: The underappreciated conceptual scheme. *Informing Science: The International Journal of an Emerging Transdiscipline, 14*, 1-32. https://doi.org/10.28945/1348

Gill, T. G. (2012). Informing on a rugged landscape: Homophily versus expertise. *Informing Science: The International Journal of an Emerging Transdiscipline, 15,* 49-91. https://doi.org/10.28945/1560

Gill, T. G. (2015). *Informing Science Volume One: Concepts and Systems*. Informing Science Press.

Gill, T. G., & Mullarkey, M. (2017). Fitness, extrinsic complexity and informing science. *Informing Science: The International Journal of an Emerging Transdiscipline, 20*, 37-61. https://doi.org/10.28945/3668

Gould, S. J., & Eldredge, N. (1972). Punctuated equilibria: An alternative to phyletic gradualism. *Models in Paleobiology*, 1972, 82-115. https://doi.org/10.5531/sd.paleo.7

Hærem, T., Pentland, B. T., & Miller, K. D. (2015). Task complexity: Extending a core concept. *Academy of Management Review*, *40*(3), 446-460. https://doi.org/10.5465/amr.2013.0350

Hargittai, E., Piper, A. M., & Morris, M. R. (2019). From internet access to internet skills: Digital inequality among older adults. *Universal Access in the Information Society, 18(4)*, 881-890. https://doi.org/10.1007/s10209-018-0617-5

Iannacci, F., Fearon, C., Kawalek, P., & Simeonova, B. (2022). Aligning the Qualitative Comparative Analysis (QCA) counterfactual approach with the practice of retroduction: Some preliminary insights. *Information Systems Journal*. https://doi.org/10.1111/isj.12409

Inglesant, P., Holter, C. T., Jirotka, M., & Williams, R. (2021). Asleep at the wheel? Responsible innovation in quantum computing. *Technology Analysis & Strategic Management, 33*(11), 1364-1376, https://doi.org/10.1080/09537325.2021.1988557

Kaplan, J., & Kiersz, A. (2021, October 12). The top 1% officially have more money than the whole middle class. *Business Insider*. https://www.businessinsider.com/top-1-have-more-money-than-the-middle-class-2021-10

Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution*. Oxford University Press.

Kitchens, B., Johnson, S. L., & Gray, P. (2020). Understanding echo chambers and filter bubbles: The impact of social media on diversification and partisan shifts in news consumption. *MIS Quarterly, 44*(4). https://doi.org/10.25300/MISQ/2020/16371

Lauterbach, J., Mueller, B., & Kahrau, F. (2020). Achieving effective use when digitalizing work: The role of representational complexity. *MIS Quarterly, 44*(3). https://doi.org/10.25300/MISQ/2020/14583

Levin, B., & Downes, L. (2023, 19 May). Who is going to regulate AI? *Harvard Business Review*. https://hbr.org/2023/05/who-is-going-to-regulate-ai

Levinthal, D. A. (1997). Adaptation on rugged landscapes, *Management Science*, 43(7), 934-950. https://doi.org/10.1287/mnsc.43.7.934

Liang, H., Peng, Z., Xue, Y., Guo, X., & Wang, N. (2015). Employees' exploration of complex systems: An integrative view. *Journal of Management Information Systems*, *32*(1), 322-357. https://doi.org/10.1080/07421222.2015.1029402

Longoni, C., Fradkin, A., Cian, L., & Pennycook, G. (2022, June). News from generative artificial intelligence is believed less. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 97-106). https://doi.org/10.1145/3531146.3533077

Magness, P. W. S., & Waugh, D. (2022/2023). The hyperpoliticization of higher ed: Trends in faculty political ideology, 1969–present. *The Independent Review 27(3)*. 359-369. https://www.independent.org/pdf/tir/tir_27_3_05_magness.pdf

Malgonde, O., Zhang, H., Padmanabhan, B., & Limayem, M. (2020). Taming complexity in search matching: two-sided recommender systems on digital platforms. *MIS Quarterly*, 44(1). https://doi.org/10.25300/MISQ/2020/14424

Markus, M. L., & Rowe, F. (2018). Is IT changing the world? Conceptions of causality for information systems theorizing. *MIS Quarterly, 42(4)*, 1255-1280.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR), 54*(6), 1-35. https://doi.org/10.1145/3457607

Meingast, M., Roosta, T., & Sastry, S. (2006, August). Security and privacy issues with health care information technology. In *2006 International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 5453-5458). IEEE. https://doi.org/10.1109/IEMBS.2006.260060

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81-97. https://doi.org/10.1037/h0043158

Mitchell, A. (2022). Professor catches student cheating with ChatGPT: 'I feel abject terror'. https://nypost.com/2022/12/26/students-using-chatgpt-to-cheat-professor-warns/

Nawir, M., Amir, A., Yaakob, N., & Lynn, O. B. (2016, August). Internet of Things (IoT): Taxonomy of security attacks. In *2016 3rd International Conference on Electronic Design (ICED)* (pp. 321-326). IEEE. https://doi.org/10.1109/ICED.2016.7804660

O'Donnell, E., Koch, B., & Boone, J. (2005). The influence of domain knowledge and task complexity on tax professionals' compliance recommendations. *Accounting, Organizations and Society, 30*, 145–165. https://doi.org/10.1016/j.aos.2003.12.003

Oedzes, J. J., Van der Vegt, G. S., Rink, F. A., & Walter, F. (2019). On the origins of informal hierarchy: The interactive role of formal leadership and task complexity. *Journal of Organizational Behavior*, *40*(3), 311-324. https://doi.org/10.1002/job.2330

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Broadway Books.

Park, Y., & Mithas, S. (2020). Organized complexity of digital business strategy: A configurational perspective. *MIS Quarterly, 44*(1). https://doi.org/10.25300/MISQ/2020/14477

Payne, B. R., Jackson, J. J., Noh, S. R., & Stine-Morrow, E. A. (2011). In the zone: Flow state and cognition in older adults. *Psychology and Aging, 26*(3), 738-743. https://doi.org/10.1037/a0022359

Pentland, B. T., Liu, P., Kremser, W., & Hærem, T. (2020). The dynamics of drift in digitized processes. *MIS Quarterly, 44*(1). https://doi.org/10.25300/MISQ/2020/14458

Pergola, J. (2014, February). Music education in crisis. *School Band & Orchestra Magazine*. https://www.nemc.com/resources/articles/music-education-in-crisis

Pinel, F. (2015). What's cooking with Chef Watson? An interview with Jav Varshney and James Briscione. *IEEE Pervasive Computing, 14*(4), 58-62. https://doi.org/10.1109/MPRV.2015.66

Popper, K. R. (1963). Science as falsification. In K. R. Popper, *Conjectures and Refutations* (pp. 33-39).

Ragnedda, M., Ruiu, M. L., & Addeo, F. (2022). The self-reinforcing effect of digital and social exclusion: The inequality loop. *Telematics and Informatics, 72,* 101852. https://doi.org/10.1016/j.tele.2022.101852

Ramponi, M. (2022). How ChatGPT actually works. *AssemblyAI*. https://www.assemblyai.com/blog/how-chatgpt-actually-works/

Robards, B. (2018). Belonging and neo-tribalism on social media site Reddit. In A. Hardy, A. Bennett, & B. Robards (Eds), *Neo-tribes* (pp. 187-206). Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-319-68207-5_12

Rosenblatt, K. (2023). ChatGPT passes MBA exam given by a Wharton professor. *NBC News*. https://www.nbcnews.com/tech/tech-news/chatgpt-passes-mba-exam-wharton-professor-rcna67036

Salo, M., Pirkkalainen, H., Chua, C. E. H., & Koskelainen, T. (2022). Formation and mitigation of technostress in the personal use of IT. *MIS Quarterly, 46*. https://doi.org/10.25300/MISQ/2022/14950

Sambasivan, N., & Veeraraghavan, R. (2022, April). The deskilling of domain expertise in AI development. In *CHI Conference on Human Factors in Computing Systems* (pp. 1-14). https://doi.org/10.1145/3491102.3517578

Sandberg, J., Holmström, J., & Lyytinen, K. (2020). Digitization and phase transitions in platform organizing logics: Evidence from the process automation industry. *MIS Quarterly, 44*(1). https://doi.org/10.25300/MISQ/2020/14520

Shiffrin, R. M., & Dumais, S. T. (1981). The development of automatism. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 111-140). Erlbaum.

Shiohira, K. (2021). Understanding the impact of artificial intelligence on skills development. *Education 2030. UNESCO-UNEVOC International Centre for Technical and Vocational Education and Training.* 1-56.

Shu, Q., Tu, Q., & Wang, K. (2011). The impact of computer self-efficacy and technology dependence on computer-related technostress: A social cognitive theory perspective. *International Journal of Human-Computer Interaction*, *27*(10), 923-939. https://doi.org/10.1080/10447318.2011.555313

Srikanth, R. P. (2017, Feb 20). Blockchain at its core targets disintermediation. *Express Computer.* https://www.proquest.com/trade-journals/blockchain-at-core-targets-disintermediation/docview/1869920924/se-2

Streufert, S., & Streufert, S. C. (1978). *Behavior in the complex environment.* Wiley.

Taleb, N. N. (2007). *The black swan: The impact of the highly improbable* (Vol. 2). Random House.

Tanriverdi, H., Rai, A., & Venkatraman, N. (2010). Research commentary—reframing the dominant quests of information systems strategy research for complex adaptive business systems. *Information Systems Research*, *21*(4), 822-834. https://doi.org/10.1287/isre.1100.0317

Te'eni, D. (1989). Determinants and consequences of perceived complexity in human-computer interaction. *Decision Sciences, 20*, 166-181. https://doi.org/10.1111/j.1540-5915.1989.tb01405.x

Teixeira de Melo, A., Caves, L. S. D., Dewitt, A., Clutton, E., Macpherson, R., & Garnett, P. (2020). Thinking (in) complexity:(In) definitions and (mis) conceptions. *Systems Research and Behavioral Science, 37(1),* 154-169. https://doi.org/10.1002/sres.2612

Townsend, R. B., & Bradburn, N. (2022). The state of the humanities circa 2022. *Daedalus, 151*(3), 11–18 https://doi.org/10.1162/DAED_a_01925

Turel, O. (2021). Technology-mediated dangerous behaviors as foraging for social–hedonic rewards: The role of implied inequality. *MIS Quarterly, 45*(3), 1249-1286. https://doi.org/10.25300/MISQ/2021/16353

Wood, R. E. (1986). Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes, 37*(1), 60-82. https://doi.org/10.1016/0749-5978(86)90044-0

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