AN EXTENSION OF THE THEORY OF TECHNOLOGY DOMINANCE: UNDERSTANDING THE UNDERLYING NATURE, CAUSES, AND EFFECTS

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Abstract

The Theory of Technology Dominance (TTD) provides a theoretical foundation for understanding how intelligent systems impact human decision-making. The theory has three phases with propositions related to (1) the foundations of reliance, (2) short-term effects on novice versus expert decision-making, and (3) long-term epistemological effects related to individual deskilling and profession-wide stagnation. In this theory paper, we propose an extension of TTD, that we refer to as TTD2, primarily to increase our theoretical understanding of how, why, and when the short-term and long-term effects on decision-making occur and why advances in technology design have exacerbated some weaknesses and eroded some benefits. Recently, researchers have called for reconsideration of how we design intelligent systems to mitigate the detrimental effects of technology; in TTD2 we provide a theory-based understanding for reimagining how such systems are designed.

Key words: Technology Dominance, Deskilling, Automation Bias, Transactive Memory Systems, Intelligent Systems, Intelligent Decision Aids, Algorithm Aversion

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1. INTRODUCTION

In many respects, the recent advances in AI-based intelligent systems[1] to support knowledge work are viewed as new and novel. Yet, as we emerge from the "AI winter" (the period when AI seemed to stall) (Susskind and Susskind, 2015; Sutton et al., 2016), the functional nature of those systems lives on and are rapidly expanding (Jasimuddin et al., 2012; Susskind and Susskind, 2015). A mid-1980s definition of expert systems focused on "the use of computer technology to make scarce… expertise and knowledge more widely available and more easily accessible" (Susskind and Susskind, 2015, 184). Using this functional definition, the progress to date can and should be regarded more favorably. Contemporary systems use different forms of knowledge representation, but the functional definition is the same and the goal is the same—distribute scarce expertise and knowledge through the best available techniques that leverage the ever-increasing computer power (Susskind and Susskind, 2015).

The Theory of Technology Dominance (TTD) was developed in this earlier time of AI-based intelligent systems to provide a foundation for understanding the conditions under which professional knowledge-workers with various skill levels were willing/unwilling to rely on intelligent systems, and for understanding the short-term implications for decision success/failure along with potential long-term negative effects on users' decision-making capabilities (Arnold and Sutton, 1998). The theory endeavored to understand why the major professional services firms, that only a decade earlier, were espousing intelligent systems as a vital component of reducing labor costs and sharing expertise had all but abandoned their efforts to develop and deploy such systems (Elliott and Jacobsen, 1987; Willingham and Ribar, 1988; Susskind and Susskind, 2015). Arnold and Sutton (1998) sought to explain both "Why intelligent systems had such limited success?" and "How might intelligent systems be more effectively deployed in knowledge

[1] Intelligent Systems is the generalized term used for a myriad of systems that integrate artificial intelligence (AI) techniques to provide intelligent advice/guidance to users. These systems cover a range of applications and terminology, including among others: expert systems, knowledge-based systems, knowledge management systems, intelligent decision aids, intelligent decision support systems, AI-based data analytics, and the arena of algorithmic decision-making.

work environments?" The theory put forth a series of propositions to explain the conditions under which professional knowledge workers would rely on these intelligent systems and to predict when success/failure was likely to occur from knowledge worker reliance. Much of the research testing the theory has focused on the existence of the detrimental impacts on decisions and associated deskilling effects (Triki and Weisner, 2014).

Knowing the conditions under which these deleterious effects occur allows somewhat for avoidance techniques, but do not necessarily provide insight on designing systems that eliminate the issues. Balasubramanian et al. (2017) argue that we know technology dominance and other associated deleterious effects exist, and researchers should shift their efforts toward designing systems that mitigate these effects. Unfortunately, many of Balasubramanian et al.'s (2017) identified suggestions (e.g. slowing technology so users ponder tasks more) are unacceptable in professional knowledge work situations that focus on efficient work processes. Asatiani et al. (2019) approach these concerns with a focus on productive knowledge work, and leverage three organizational cases studies on automation tool use and associated impacts on distributed cognition and associated deskilling effects to develop recommendations for rethinking intelligent systems' design. These recommendations recognize the need for distributed cognition between human-computer dyads, and the need to keep the human involved even as automated processes replace much of the mundane task completion. The recommendations also elucidate our limited understanding of the underlying cognitive processes that lead to technology dominance and the inherent deskilling effects. While Asatiani et al. (2019) reiterate that these negative phenomena occur, a good theoretical understanding of how and why interactions with intelligent systems lead to deleterious effects on human expertise has not been proposed; this understanding seems necessary to effectively implement intelligent systems that address technology dominance concerns (Sutton et al., 2016; 2018).

The purpose of this theory extension is to explore the cognitive processes that can cause technology dominance to occur and to understand how and why deskilling invariably occurs with the prolonged use of intelligent systems in professional knowledge work environments. We develop an extended model of TTD that integrates literature across numerous research disciplines (e.g., auditing, human factors/ergonomics, information systems, insolvency, medicine, neuroscience, psychology) to provide a deep exploration of the underlying causes of technology dominance and to better understand why certain technology characteristics and constructions exacerbate the problems. We propose an extended theory, referred to as TTD2, which provides a foundation for exploring the underlying causes and creates a theory-based vision for systems design that might counteract these underlying deleterious effects through new specifications of constructs and methods.

While TTD has been applied to several knowledge-work domains, the primary focus of the theory has always been on the professions (Arnold and Sutton, 1998). The focus on the professions comes from the core environment promoting the development of expertise among its members, the formation of firms of professionals that provide a cost-effective environment for the development of advanced AI-based intelligent systems, and the ability of such firms to provide barriers of entry to competitors. The most common of these professional firms exist in auditing, consulting, engineering, insolvency, law, medicine, and tax advising (Susskind and Susskind, 2015). All these professions are rapidly adapting intelligent systems that are radically reshaping the way decisions are made, using paraprofessional models that match novices with intelligent systems, and reimagining how their services can be delivered (Susskind and Susskind, 2015). Yet, as we spring from the "AI winter", we lack a detailed theoretical understanding of how these systems alter decision-making processes and outcomes, and the impact these systems have on the capabilities of knowledge workers in these professions, as well as the firms in which they work.

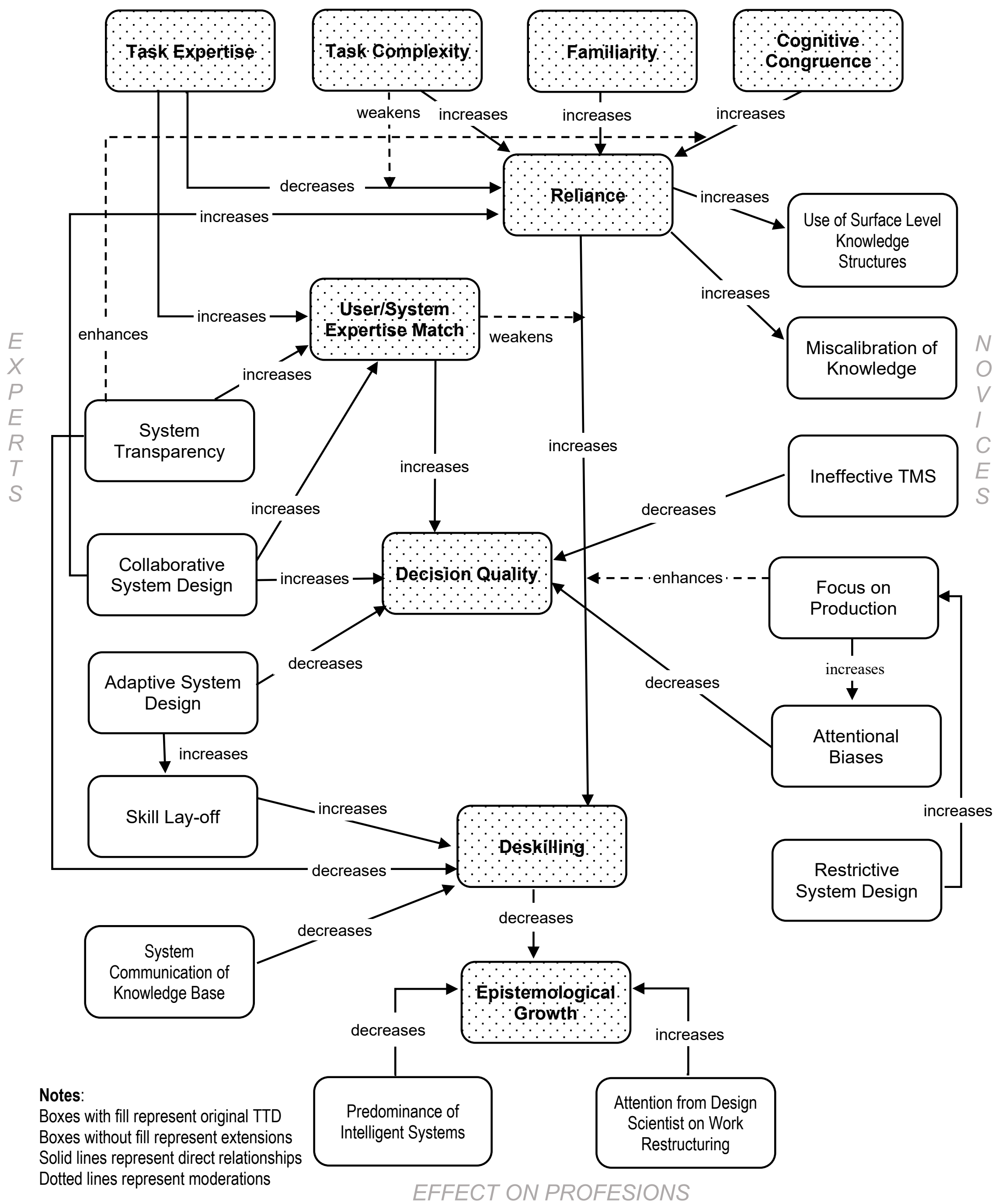
The following sections of the paper systematically address the three phases of TTD: reliance/non-reliance, short-term decision effects, and long-term deskilling and epistemological stagnation. Phase I of TTD relates to reliance/non-reliance on intelligent systems, addressing a precursor to Technology Dominance—dominance *only* occurs if a user relies on the system. The four propositions underlying reliance in TTD have proven quite robust; and, in our formulation of TTD2, the changes to these four propositions are minor and are designed to primarily address terminology issues that have arisen in the related research. Our extension of TTD focuses on the second two phases which are the "technology dominance" portion of TTD. Phase II explores in greater depth the theoretical foundations for how and why technology dominance persists in decision-makers' judgments in order to provide a better theoretical understanding of the underlying nature, causes, and effects on professional decision-making. Phase III focuses on the long-term effects of technology dominance and explores in greater depth the theoretical foundations underlying the occurrence of deskilling and extends the theoretical understanding of how and why intelligent systems designs exacerbate these problems.

2. DEVELOPING AN EXTENDED THEORY OF TECHNOLOGY DOMINANCE (TTD2)

To better understand how and why technology dominance effects persist, an exploration of the related literature was undertaken. Many researchers in many disciplines (e.g. auditing, human/factors and ergonomics, insolvency, medicine, neuroscience, psychology) have been exploring a similar set of cognitive processing issues from multiple perspectives. TTD2 is enriched by drawing from all these disciplines and is the product of a literature/theory review across the multiple disciplines to develop a cohesive model. This search began with a review of all citations of the original TTD paper, a branching out to the theories integrated by researchers into TTD for their specific studies, and similar branching analysis from the Sparrow et al. (2011) *Science* paper on the "google effect". Additionally, the researchers did a detailed exploration of the contemporary expertise literature to develop a strong understanding of the various schools of thought on how expertise is developed and the key cognitive components that must come together to develop expertise.

An overall summary of TTD2 is presented in Figure 1 and discussed in detail over the following sections. The original theory is represented by the shaded components of the diagram. The extensions put forth in TTD2 come from three perspectives: (1) the interactive effects of intelligent systems and novice users, (2) the interactive effects of intelligent systems and expert users, and (3) the interactive effect of contemporary professional firms' adoption of intelligent systems and the nature of epistemological growth within the professional domain. Each of these aspects are set forth in Phase II and Phase III, but first we review the reliance portion of the theory (Phase I) which is a necessary precursor to the technology dominance portions of the theory coming to fruition.

FIGURE 1: The Theory of Technology Dominance Extended—TTD2



3.0 PHASE I: THE RELIANCE MODEL

The reliance portion of TTD (and TTD2) consists of four propositions (see Table 1); while that represents half of the propositions, reliance itself is not a part of technology dominance. Rather, reliance is a necessary pre-condition for dominance to occur. There is greater pressure for reliance in the contemporary knowledge work environment as increasingly professional firms mandate usage of specific intelligent systems during performance of work tasks (Dowling and Leech, 2014; Dowling et al., 2018; Boland et al., 2019). However, reliance is still key in that it is not a dichotomous decision, but rather a continuum. Within the context of TTD, reliance is defined as the user's incorporation of the intelligent system's processes and outputs when formulating their own decision—the system becomes part of the decision-making process and exerts influence on decision outcomes.[2] Accordingly, the basic assumption is that the user/system decision process must be interactive, a human-computer dyad. In TTD, the computer is referred to as the 'electronic colleague' where there is an assumption that each will take part in the collaborative decision-making process (Arnold and Sutton, 1998).

Table 1: Comparison of Propositions from TTD1 and. TTD 2

TTD1 Propositions	TTD2 Propositions
Phase I: The Reliance Model	
Proposition 1: When users have a low to moderate level of experience, there is a negative relationship between task experience and reliance on a decision aid.	*Proposition 1:* When users have a low to moderate level of experience, there is a negative relationship between task experience and reliance on an intelligent system.
Proposition 2: There is a positive relationship between task complexity and reliance on a decision aid.	*Proposition 2*: When users have a moderate to high level of experience, there is a positive relationship between task complexity and reliance on an intelligent system.
Proposition 3: When task experience and perceived task complexity are high, there is a positive relationship between decision aid familiarity and reliance on the decision aid.	*Proposition 3*: When users have a moderate to high level of experience and perceived task complexity is high, there is a positive relationship between familiarity with an intelligent system and reliance on the system.

[2] Note that the focus on reliance is about the incorporation of intelligent systems' processes and outcomes into a knowledge worker's judgment and decision processes, a very specialized and parsimonious theorization. This is quite different from the generalized concepts of technology acceptance and use that focus on the willingness to adopt and use an available technology, particularly commercially available applications. There are very robust models that effectively capture this phenomenon (Blut et al., 2022; Hardin et al., 2022).

TTD1 Propositions	TTD2 Propositions
Proposition 4: When task experience and perceived task complexity are high, there is a positive relationship between cognitive fit and reliance on the decision aid.	*Proposition 4*: When users have a moderate to high level of expertise, familiarity with an intelligent system and perceived task complexity are high, there is a positive relationship between cognitive congruence and reliance on an intelligent system.
Phase II: Short-Term Technology Dominance Effects	
Proposition 5: When the expertise of the user and intelligent system are mismatched, there is a negative relationship between the user's expertise level and the risk of poor decision-making.	*Proposition 5*: When the expertise of the user and intelligent system are mismatched, there is a negative relationship between the user's expertise level and the risk of poor decision-making. *Proposition 5a*: Creation of ineffective TMS when engaging with intelligent systems leads to increased risk of poorer decision-making. *Proposition 5b*: Novices expend more cognitive energy on completing systems tasks than the underlying decision-making processes. *Proposition 5c*: As more energy is focused on completing tasks, novices will succumb to attentional biases that increases complacency and commission/omission errors. *Proposition 5d*: Novices increase mis-calibration of their knowledge and skills when using intelligent systems. *Proposition 5e*: Increased systems restrictiveness in guiding user activities increases novice user activation of surface-level knowledge and focus on task completion. *Proposition 5f*: Novices use surface-level as opposed to deep-knowledge structures when using intelligent systems.
Proposition 6: When the expertise level of the user and intelligent systems match, there is a positive relationship between reliance on the aid and improved decision-making.	*Proposition 6:* When the expertise level of the user and intelligent systems match, there is a positive relationship between reliance on the aid and improved decision-making. *Proposition 6a*: As the collaborative design of an intelligent system increases, reliance on the system will be positively related to an expert's decision quality. *Proposition 6b*: As the collaborative design of an intelligent system increases, an expert user's reliance on and engagement with the system will increase.

TTD1 Propositions	TTD2 Propositions
	Proposition 6c: The greater the transparency in how a system uses information to generate decision recommendations, the better the collaborative relationship with an experienced decision-maker. *Proposition 6d*: Adaptive systems allowing expert users to opt in/out of collaboration when they trust the system may have short-term benefits, but over time experts will stop participating. *Proposition 6e*: Extended skill layoffs from experts opting out of collaboration on system supported decisions increasingly place the expert at a more novice level, increasing susceptibility to concerns raised with novice decision-maker use of intelligent systems.
Phase III: Long-Term Technology Dominance Effects	
Proposition 7: There is a positive relationship between continued use of an intelligent decision aid and the de-skilling of auditors' abilities for the domain in which the aid is used.	*Proposition 7:* There is a positive relationship between continued use of an intelligent decision aid and the de-skilling of auditors' abilities for the domain in which the aid is used. *Proposition 7a*: The more that intelligent systems allow novices to focus purely on production activities, the poorer the knowledge structures that will be developed by the user. *Proposition 7b*: The more that intelligent systems are designed to communicate structural pattern data to novice users, the better the knowledge structures that will be developed by the user. *Proposition 7c*: The more that intelligent systems allow experts to have skill-layoffs, the greater the likelihood of attrition of the user's expertise. *Proposition 7d*: The less transparent that an intelligent system is in providing an experienced decision-maker with an understanding of how information is used in a decision and how decisions are formulated, the greater the risk of deskilling the user. *Proposition 7e*: The use of unexplainable artificial intelligence techniques in intelligent systems supporting experienced decision-makers will increase the risk of deskilling the user.

TTD1 Propositions	TTD2 Propositions
Proposition 8: There is a negative relationship between the broad-based, long-term use of an intelligent decision aid in a given problem domain and the growth in knowledge and advancement of the domain.	*Proposition 8:* There is a negative relationship between the broad-based, long-term use of an intelligent decision aid in a given problem domain and the growth in knowledge and advancement of the domain. *Proposition 8a*: Human discourse on improvement and evolution of a profession will stagnate in the presence of prolonged use of intelligent systems. *Proposition 8b*: Use of intelligent systems in a profession may trigger epistemological change through advances in design theory and innovative techniques. *Proposition 8c*: The more predominant intelligent systems become in a profession, the greater the deprofessionalization of that profession.

While the four reliance propositions in TTD are intended to work simultaneously and are necessary for reliance to occur in expert decision-makers, Hampton (2005) is the only experimental study that has tested all four propositions simultaneously and Goddard et al. (2014) to test at least three, likely because of the experimental complexity and number of participants required. Both studies find strong support for the propositions except for familiarity. All participants assessed familiarity as 'high' and the lack of deviation in responses prevented analysis of this dimension. Williams (2020) does test the full reliance model through archival decision data and the results provide strong support for all dimensions of the reliance model.[3]

More commonly, studies use one or two of the propositions in more targeted studies of reliance and with a focus on extending or clarifying the four propositions. Several of these studies have importance to understanding TTD's reliance model. For instance, Jensen et al. (2010) found that novices relied on a intelligent decision aid much more than experts, but that experts did rely to some degree. Surprisingly, however, they found no evidence that the experts pursued information available in the intelligent system that would provide

[3] Williams (2020) examined over 100,000 credit risk assessments and while they did not measure task complexity, they measured decision aid complexity by the number of information cues used in the assessment algorithm. Decision aid complexity could arguably be perceived as a measure of task complexity given the cues used in the algorithm should be an indicator of the complexity of the task being performed.

familiarity with the strategies used and would allow the experienced user to establish cognitive fit. The results suggest that improving transparency in intelligent systems design should be carefully considered.

Al-Natour et al. (2008) capture a perhaps more salient concern with the cognitive fit dimension of the theory. In TTD, cognitive fit is defined as “the degree to which the cognitive processes used with the decision aid to complete or solve a task match the cognitive processes normally used by an [expert] decision-maker” (Arnold and Sutton, 1998). There is an inherent assumption in this definition that an expert will know the optimal match between decision strategy and successful decision outcome. However, most TTD studies have used experienced decision-makers that are generally not considered experts. While the theory holds, it also suggests that this optimization will not always be identified by the user. As such, this matching of experienced users with the processes used by the intelligent system will likely fall short of Vessey’s (1991) established definition of cognitive fit requiring that the actual optimal decision model be incorporated in the intelligent system. Al-Natour et al. (2008) avoid relying on cognitive fit with this disconnect, and instead focus on “perceived decision process similarity” and “perceived decision outcome similarity” which are assessments by the user based on the congruence between the intelligent system and their own preferred assessment approach. We view this construct as more accurately depicted as *cognitive congruence*, a condition where the schema of the user matches with the schema of the collective, which in this case is embodied in the intelligent system. This match in schema is critical to establish *cognitive congruence* (Merali, 2000). This is encoded in TTD2 through a revision of proposition #4 to focus on congruence rather than fit (see Table 1 and Figure 2).

Propositions 1-4 are slightly refined in TTD2 and are presented in Table 1, with the following refined definitions also being key to interpretation of the model constructs in Figure 2.

reliance = *f* (task expertise, task complexity, decision aid familiarity, cognitive congruence)

where:

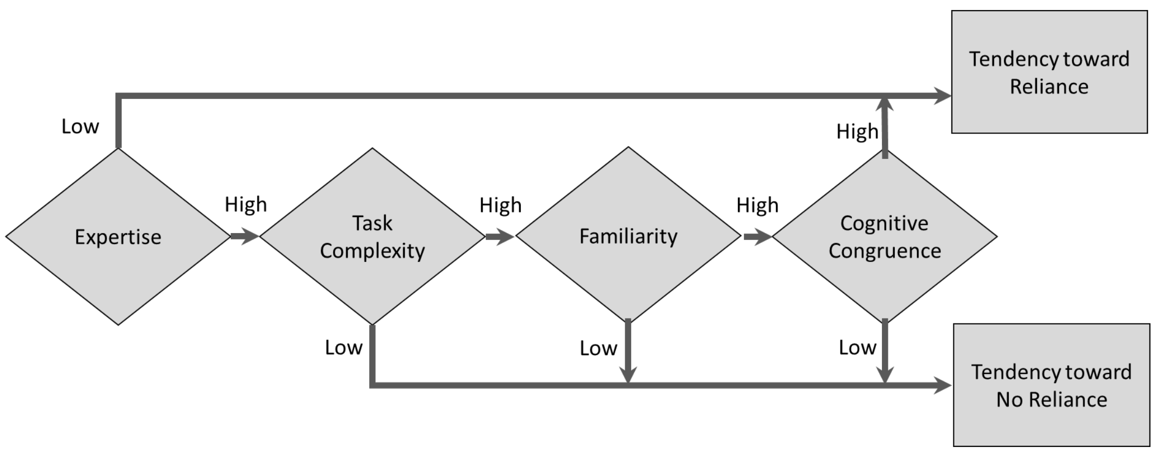
reliance is the incorporation of an intelligent system into the judgment and decision-making process, such that the system’s processes and outputs are considered when formulating one’s own decision, *expertise* is the level of expertise (ranging from novice to expert) that a decision-maker has with respect to completion of a given decision task and the degree to which the decision-maker has formed strategies for completing or solving the task,

task complexity is the degree to which task completion or resolution taxes the cognitive abilities of the decision-maker,

familiarity is the degree to which a user is comfortable with a given decision aid based on prior experience and/or training in using the given decision aid (or similar), and

cognitive congruence is the degree to which the cognitive processes used by the intelligent decision aid to complete or solve a task match the cognitive processes that the user would perceive to be normally used by an expert decision-maker.

FIGURE 2: The Reliance Model



Source: Arnold and Sutton, 1998

Figure 2 is intended to highlight the decision nature of each dimension of reliance with differential effects from high or low levels of the constructs of interest. The diagram has often been interpreted as a process model requiring dependencies among these conditions, but reliance is a function of the four constructs that will differ under varying conditions. Under repeated use, an experienced decision maker may balance the complexity of the decision with their familiarity and comfort with the cognitive congruence of the system in deciding whether to rely.

3.1 Algorithm Aversion/Appreciation

We feel it is prudent to briefly address the psychology theory around algorithm aversion and algorithm appreciation that has recently arisen. For many long-term researchers in intelligent systems and artificial intelligence, these issues are viewed as 'old wine in new bottles' as the research of the 1980s and 1990s reappear as new (see Brown and Eining, 1997; Rose, 2002). However, algorithm aversion has captured the imagination of researchers and become a bit of popular culture and business press folklore (Frick, 2015; Harrell, 2016; Logg et al., 2019). Herein, we choose to focus on commonalities with TTD and what TTD has to offer the research stream.

Algorithm aversion (Dietvorst et al., 2015) and algorithm appreciation (Logg et al., 2019) can be viewed as lying on the non-reliance/reliance continuum respectively. The dimension that is most different in the discourse is perhaps the focus on choosing algorithmic advice versus human advice and that aspect is outside of TTD. TTD works under the assumption that most knowledge workers in professional firms are presented with an intelligent system to assist them in their work and that system becomes an 'electronic colleague' as a replacement colleague, not as an optional other. This is consistent with the research on established audit practice implementations through audit support systems with embedded intelligent components (Dowling and Leech, 2014; Dowling et al., 2018; Boland et al., 2019).

Dietvorst et al. (2015) are generally credited with coining the term 'algorithm aversion' (Logg et al., 2019). However, even Dietvorst et al. (2016) quickly followed with evidence that if you let people interact with algorithms, even if the user's input is limited by the system, algorithm aversion dissipates. In knowledge work environments, such systems are almost always interactive and the literature on TTD has focused on interactive systems (Triki and Weisner, 2014) with an emphasis on the use of collaborative systems (Arnold and Sutton, 1998; Sutton et al., 2021). Absent this interactive nature and an ability of the user to contribute to the decision-making process, an expert user faces limited *familiarity* and unknown *cognitive congruence*. The need for *cognitive congruence* when working with data analytics, a common form of algorithmic decision-making studied in the knowledge work arena, provides a probable explanation for the findings in Koreff (2022) where experienced auditors show a preference for different types of analytics based on whether financial or non-financial information is being analyzed.

Logg et al. (2019) argue that algorithm aversion is a rare event—most people prefer algorithms and exhibit algorithm appreciation. Among their experiments, they specifically consider the ingrained nature of algorithm aversion lore among researchers. When academic researchers were asked to predict the results of their experiments, they consistently (over 85%) believed the results would show aversion when in fact the results indicated appreciation. Through a series of seven experiments, Logg et al. (2019) systematically examine the attributes that differentiate between aversion and appreciation outcomes. They found that regardless the level of subjectivity of the decision and the nature of the competing advice, participants consistently demonstrated algorithm appreciation—unless they were experienced professional decision-makers (consistent with Proposition 1 of *expertise* effects on reliance). Other evidence, however, suggests that aversion is diminished as a user gains experience with an algorithm. Filiz et al. (2021) find that using an algorithm for stock price increase/decrease that is 70% effective, participants in repeated trials learned that the algorithm was better performing than they were and quickly adopted the algorithms. This again seems consistent with TTD's view that *familiarity* and *task complexity* will influence reliance.

The algorithm aversion/appreciation literature is relatively new in its development. Over time, as more studies are conducted, a clearer picture is likely to evolve—although theoretically there is certainly an argument that the findings should not be much different than the earlier intelligent systems and artificial intelligence findings (Rose, 2002; Susskind and Susskind, 2015). Jussupow et al. (2020) synthesize the research to date to find patterns in the results and formulate preliminary propositions. *Expertise* is a significant determinant with more experienced decision-makers being less likely to exhibit appreciation. Decision-makers exhibit less appreciation for performative algorithms than they do advisory algorithms (which are most likely to be used in professional knowledge work settings). Experience with the algorithm that yields performance enhancements over the human decision-maker alone leads to appreciation (*familiarity*). This performance accomplishment over time further enhances appreciation as the decision-maker views the algorithm as capable of performing the task (*cognitive congruence*). Jussupow et al. (2020) also address dimensions that would be outside the purview of TTD: if a human is involved in the development of an algorithm there is more appreciation; and, the greater the social distance from a human alternative, the more likely individuals are to choose the human over the algorithm.

4.0 PHASE II: SHORT-TERM TECHNOLOGY DOMINANCE EFFECTS

TTD is a theory about the strong role that technology plays when humans are matched with intelligent systems. Accordingly, the dominance portion of the theory has drawn the attention of researchers who have unveiled the presence of technology dominance across multiple knowledge work domains. Two related propositions in the original TTD differentiate between the expected impacts of intelligent systems on novice versus expert users[4]:

> *Proposition 5:* When the expertise of the user and intelligent system are mismatched, there is a negative relationship between the user's expertise level and the risk of poor decision-making.

> *Proposition 6:* When the expertise level of the user and intelligent systems match, there is a positive relationship between reliance on the aid and improved decision-making.

Arnold and Sutton (1998) theorize the concerns over novice use of intelligent systems arise from the inevitable focus on the business benefit of intelligent systems in capturing large knowledge bases of complex information and highly subjective relationships (i.e., expertise)—the type of knowledge base (expertise) that novices desire to attain, but do not cognitively possess. When these systems are put in the hands of novices, the reliability of the system is in part based on the reliability of the inputs to the system—the data gathering and interpretation that must be completed by the novice user. Further, when the advice/output of the system is received, the novice user does not have the requisite knowledge to consider the reasonableness of the intelligent system's response. In the past, this has largely been written off as overreliance, a broad, general category of decision behavior.

Arnold and Sutton (1998) theorize that optimal outcomes are more likely to occur when experts as opposed to novices use an intelligent system (Proposition 6). This assumes collaborative systems' design where the system and expert user will trade control of the decision process, each providing input and direction while the human maintains some level of control of the decision process. Arnold and Sutton (1998) advocate the *electronic colleague* model whereas the relationship mimics how two human experts interact, share perspectives, and provide different knowledge and recommendations. Past research

[4] Note that both propositions are premised on the assumption of reliance on the intelligent system by the novice/expert user. Thus, as noted in the discussion of Phase I, reliance is a necessary precursor for Propositions 5 and 6 to occur.

indicates that dyads make better decisions than individuals (Trotman et al., 1983). The concept builds off work in the design of intelligent systems that focus on constructive dialogue to engage the user in the decision-making process (Eining et al., 1997; Arnold and Sutton, 1998). This focus on the electronic colleague is viewed as improving decision outcomes through the collaborative nature of the interaction and avoids the negative effects identified when either the computer or the human dominates the decision process (Hale and Kasper, 1989).

These aspects of the theory have held well in testing across multiple domains, although recently we see more questionable results with Proposition #6, which as we will discuss, appear to arise from the failure to use collaborative decision models. For example, in the tax compliance arena, we find that novices make detrimental decisions when facing certain system prompts whereas more experienced decision-makers digest the prompts, but do not overreact (Masselli et al., 2002; Noga and Arnold, 2002). Similarly, a study of insolvency (bankruptcy) professionals found that an intelligent system leads to overreaction and greater decision bias in novices, while experts used the collaboration and advice to temper normally existing decision biases (Arnold et al., 2004). Seow (2011) showed that systems that provided greater guidance in an internal control assessment task led to novice users missing control weaknesses unidentified by the system as compared to novices required to explore on their own. In a study of physicians using a system to facilitate patient diagnosis, physicans were found to abandon their own diagnoses if it was not one of the options proposed by the intelligent system even though in 5.2% of total cases their abandoned diagnoses were correct (although the more experienced physicians were less affected) (Goddard et al., 2014). Wortmann (2019) found that marketing innovation was stymied by an intelligent system designed to use data analytics to enhance innovation as the marketers relented purely to system-identified innovations. In a corporate finance environment, when a new system was put in place to perform a corporate tax planning task and discontinued a few years later, the people who had performed the task were no longer able to perform it on their own (Rinta-Kahila, 2018; Rinta-Kahila et al., 2018; Asatiani et al., 2019). Finally, in a qualitative study of financial statement auditors looking at junior auditors' use of data analytic tools embedded in firm audit support systems, the junior auditors admitted that they really did not know what they were doing when they completed automated tasks in the system (Stensjö, 2020). In short, across a range of knowledge work domains, the existence of technology dominance appears present.

While the observance of technology dominance seems widespread, we have limited theoretical understanding as to the underlying nature, causes, and effects of these dominance influences. As argued by Balasubramanian et al. (2017), technology dominance and other related deleterious effects are prevalent, and our research should shift to understanding why they occur so that we can design systems in a manner to mitigate the negative consequences on users. In the following sections, we extend TTD to incorporate an array of contributing affects to better understand the nature of these effects.

4.1 Novice Overreliance

There are two parallel streams of research that provide insights in explaining why technology dominance occurs in novices. Automation bias arose in the human factors/ergonomics literature around the same time that TTD appeared in the accounting and information systems literatures. Automation bias focuses on how the availability of automated decision aids feeds a human tendency to exert less cognitive effort, with the decision aid becoming a heuristic replacement for vigilant information seeking and processing (Mosier and Skitka, 1999). More recently, a *Science* paper on the "Google Effect" that posits individuals no longer store information in their brain, but simply remember where they found it, (Sparrow et al., 2011) has spurred research across a number of domains. This research has spurred interest from neuroscientists, psychologists working in the domain of transactive memory systems (TMS), and human factors/ergonomics. The fascination with Sparrow et al.'s (2011) research is perhaps best summed up by Hancock (2014) who states the question as, "Can technology induce stupidity?" TTD would suggest the answer is 'yes', but that answer is elaborated upon in the following discussion.

Automation bias is concerned with the general observation that there is something about technology that causes people to be less vigilant (Mosier and Skitka, 1999). The absence of vigilant information seeking and processing that would normally be expected of decision-makers when they are not using a decision aid escalates the occurrence of two types of errors (i.e. attentional biases): omission errors and commission errors. *Omission errors* are the failure to respond to system irregularities or events when automated systems fail to detect or indicate them (Mosier and Skitka, 1999). Seow's (2011) study where users failed to identify internal control weaknesses that were not specifically prompted by the decision aid is one example of this form of error. *Commission errors* occur when individuals incorrectly follow automated directives or recommendations without verifying them against other information or despite a contradictory source of information (Mosier and Skitka, 1999). The ingrained action orientation of automated monitoring aids is a major driver of commission errors. The example commonly referenced for commission errors is the heavy tendency for airplane pilots to respond to a cockpit warning system without analyzing the available instrumentation readings to fully understand if there is an issue, and what is the issue (Bahner et al., 2008).

Seow's (2011) study focuses on the nature of systems and the effect of systems design on the likelihood of commission errors. Participants used one of two systems, the first system requiring the user to systematically respond to the presence/absence of a set of controls (a restrictive design that forces the user through a specified analysis process) versus a system that provided a similar list of controls but allowed the user to openly list strengths and weaknesses. Users of the more restrictive system were much more susceptible to omission errors. Yet, these restrictive systems are the type of systems that are increasingly prevalent in knowledge worker environments (Dowling and Leech, 2007, 2014; Dowling et al., 2008). In their analysis of user experiences with a newly implemented restrictive system by a major audit firm, Dowling and Leech (2014) note that novice-level auditors felt they were better auditors because of the ease in which they could complete tasks compared to their predecessors. This is not surprising as research indicates that novice users prefer restrictive systems that lead them through decision tasks (Malaescu and Sutton, 2015), but such systems seemingly promote complacency in the user.

Related to automation bias, but evolving somewhat separately, is the concept of automation complacency (Parasuraman and Manzey, 2010). Complacency has been observed primarily when a set of conditions are present: (1) there is a human operator monitoring an automated system, (2) the frequency of monitoring is less than optimal, (3) the limited monitoring has a negative effect on performance, and (4) the resulting error is an omission error. Complacency is exacerbated when the user has multiple other task responsibilities, and the decision aid is consciously or subconsciously viewed as an option for offloading responsibility. Complacency is also accentuated by successful performance of the system over time. Parasuraman and Manzey (2010) make the case that complacency is a part of automation bias. Experience with reliable systems leads to automation complacency, and complacency leads to errors of omission and commission (see also Lyell and Coiera, 2017). The research on restrictive systems seems to suggest that the restrictiveness of an intelligent system builds confidence in the system and a perception of reliability as the system operates consistently, thus opening the risk of automation bias.

The work spurred by Sparrow et al's (2011) research on the "Google Effect" provides additional insight into how complacency can take hold, but also why humans are so willing to rely on technology. The work in this area centers around human use of Internet search engines, but we argue that the core psychological attributes underlying these findings should translate equally to users of other intelligent systems, namely those designed to support professional knowledge work. Sparrow et al. (2011) rely on transactive memory systems (TMS) theory as they study humans' relationship with the Internet and search engines. TMS is a theory normally associated with groups, where humans combine their own stored knowledge with that of others in their work group, understanding that the others have the additional knowledge that may be required for effective decision-making—often referenced as shared memory (Lewis and Herndon, 2011). The problem is that in human-internet relationships, the humans no longer see the need to contribute knowledge to the TMS—rather humans do not store information in their own brain, they only remember where to find the information on the Internet. Indeed, humans are losing their ability to store information in long-term memory and the brain itself is adapting as the memory portion physically shrinks and the 'how to find information' section becomes a more actively engaged part of the brain (Sparrow et al., 2011). In these TMS relationships, the Internet appears to act as a "supernormal stimulus" commandeering preexisting tendencies and reshaping cognitive behavior. The human remembers less, but believes they remember more. They also tend to latch onto the first information they find and actively avoid additional information search that might yield conflicting information, a situation that would slow their decision-making and require investment of greater cognitive effort to resolve the conflict (Ward, 2013).

The overwhelming effect of having information only an Internet search away is that humans shrink their TMS network, no longer relying on other humans (or themselves for that matter) but relying on the Internet for quick access (Fisher et al., 2015). One part of the problem is that there is a perhaps unintentional, but strongly prevalent, belief that what is found is accurate (Hancock, 2014). The human reaction is the bigger concern though, as the user becomes mis-calibrated on what they know. Users believe that they know what they have seen, and the faster they find it the more confident they are in their own knowledge of it (Fisher et al., 2015). Success in the search flows over to overconfidence in other related tasks, a general overconfidence termed an "illusion of competency" (Fisher et al., 2015). We posit that these same effects will present themselves in the intelligent systems provided to knowledge workers where such systems generally facilitate rapid access of standards, firm policies, templates for work completion, guidance on task completion, and often even work-flow control (Dowling and Leech, 2014). The novices in Dowling and Leech (2014) certainly exuded such confidence in their own abilities while being reliant on the firm's support system for task completion.

Research in neuroscience both confirms these effects and highlights other concerns. The changes taking place in the human brain suggest that the Internet is also reshaping cognition in the brain (Loh and Kanai, 2015). The focus of the research is on digital natives, younger professionals who have lived with Internet search capabilities most of their lives—with the Internet only as far away as their smart phone. The observed reshaping of the brain indicates that the portion of the brain that facilitates deep learning (i.e., the creation of deep knowledge structures in long-term memory) is shrinking, leading to shallow decision-making. Brain imaging suggests that digital natives tend to make decisions on limited information and move forward—no brain activation towards retention of the information and limited cognitive effort. These effects are exacerbated by multitasking and performance pressure (e.g. time pressure) (Loh and Kanai, 2015).

The emerging body of research across multiple disciplines suggests several cognitive processing concerns that can make novices susceptible to poorer decision making when using intelligent systems. We synthesize this research into a subset of propositions in TTD2 that appear to explain at least part of the conceptual basis for novice decision-making impacts.

> *Proposition 5a*: Novices will develop ineffective TMS when engaging with intelligent systems leading to increased risk of poor decision-making.
>
> *Proposition 5b*: Novices will expend more cognitive effort on completing system tasks than on the underlying decision-making processes.
>
> *Proposition 5c*: As more effort is focused on completing tasks, novices will succumb to attentional biases that increase complacency and/or commission/omission errors.

Proposition 5d: Novices will increasingly mis-calibrate their knowledge and skills when using intelligent systems.

Proposition 5e: As system restrictiveness in guiding user activities increases, novices will activate surface-level knowledge and focus on task completion.

Proposition 5f: Novices will use surface-level as opposed to deep-knowledge structures when using intelligent systems.

4.2 Importance of Collaborative Systems for Experts

A key attribute of Proposition #6 in TTD is the need to develop and adopt collaborative-based systems to engage experts and to leverage the duality of expertise between user and system. In essence, TTD could be interpreted as arguing that an intelligent system can work in an effective TMS relationship if the user brings equivalent knowledge to the relationship—a TMS form that is more akin to the successful TMS relationships identified in the literature. This type of relationship embodies the *electronic colleague* concept put forth in TTD as the type of relationship required for effective expert reliance, and engagement with intelligent systems (Arnold and Sutton, 1998).

The electronic colleague becomes a partner in the decision-making process—in effect transforming an individual decision-making environment into a dyadic group mode. This colleague provides advice, exchanges feedback and advice, and maintains a dialogue that facilitates the decision-maker's final judgment. The key to the successful relationship is that the system must be perceived as beneficial to the decision-maker and perceived as a knowledge asset for the decision-maker that will usefully assist in the decision process. But, there is an underlying assumption that the user will also remain engaged and active in the decision process—a key aspect of collaborative systems.

Such a collaborative system was examined by Arnold et al. (2004) using partners, directors, and managers in an insolvency decision-making task. In their study, the system was effective in reducing the decision bias in the experts' decision processes. In a follow-up study, Arnold et al. (2006) used an enhanced version of their intelligent system that includes a full set of explanations in both feedforward (help understanding what the system is doing during information aggregation) and feedback (help understanding the logic behind the systems recommendation outcomes) modes. Their results indicated that when transparency improved, experts exhibited greater reliance on the system in formulating decisions. Using tax compliance software, Masselli et al. (2002) also found improved decision making with experienced decision-makers when the system worked collaboratively to identify potential tax compliance audit risks. While the studies are limited, intelligent systems that work collaboratively with the high-expertise user appear to result in better decision-making and effectively leverage user's expertise. Accordingly, we theorize in TTD2 that:

> *Proposition 6a*: As the collaborative design of an intelligent system increases, reliance on the system will be positively related to an expert's decision quality.
>
> *Proposition 6b*: As the collaborative design of an intelligent system increases, an expert user's reliance on and engagement with the system will increase.
>
> *Proposition 6c*: The greater the transparency in how a system uses information to generate decision recommendations, the better the collaborative relationship with an expert decision-maker.

The improved decision-making from expert decision-makers using an intelligent system as put forth in TTD's Proposition #6 is premised on collaborative systems design. Collaborative systems design requires the user to be actively engaged as a co-equal partner in the decision-making process. Research in the area, however, has suggested that high-expertise users should be given more leeway in deciding when they want to be engaged and have advocated adaptive systems (Parasuraman and Wickens, 2008). Adaptive systems allow the decision-maker to choose to let the intelligent system take complete control and automatically make the decision or the user to simply rely on the system's recommendation without engaging in the decision process.

This ability to step away will initially be gradual; but, under time pressure and in multi-tasking situations, as users become more comfortable with the system's performance, the users will take greater layoffs from engagement with the decision-making (Hancock, 2014). This potentially makes expert decision-makers susceptible to automation bias as at the core of the automation bias problem is a decreased situational awareness and vigilance by the user (Mosier and Skitka, 1999). Sauer and Chavaillaz (2017) highlight this problem in their study of adaptable systems and extended skill layoffs, showing that even relatively short skill layoffs can leave the decision-maker less confident and less prepared to make decisions. Mosier and Skitka (1999) argue that system designs that do not account for the human tendency to take short-cuts cannot be considered human-centered. System designs that make skill layoffs easy exacerbate the problem, as Hancock (2014) notes, “if you build systems where users are rarely required to respond, they will rarely respond when required”.

A recent TTD study considered this skill layoff problem in a case study of an organization (Rinta-Kahila, 2018; Rinta-Kahila et al., 2018). The corporate finance department implemented an advanced system that replaced the need for staff to complete certain tax planning and compliance functions. After a few years, the organization decided to discontinue the system and restore the previous staff’s responsibilities for the task. The organization struggled as the staff was no longer competent to effectively perform the task—the skill layoff had reduced their ability to perform, essentially reflecting a de-skilling of the staff.

> *Proposition 6d*: Adaptive systems allowing expert users to opt in/out of collaboration when they are confident in relying on the system may have short-term benefits, but over time experts will stop participating.

> *Proposition 6e*: Extended skill layoffs from experts opting out of collaboration on system supported decisions increasingly place the expert at a more novice level, increasing susceptibility to concerns raised with novice decision-maker use of intelligent systems.

5.0 PHASE III: LONG-TERM TECHNOLOGY DOMINANCE EFFECTS

Technology dominance has short-term effects on the quality of decision making with novices and experts, but the longer-term effects are arguably more concerning. Two general epistemological concerns arise from intelligent systems use. At the individual level, the concern is over the deskilling effects from using such systems. At the profession level, the concern is over the long-term epistemological growth of the domain’s knowledge base. Propositions #7 and #8 of TTD address these concerns:

> *Proposition 7:* There is a positive relationship between continued use of an intelligent decision aid and the de-skilling of auditors’ abilities for the domain in which the aid is used.

> *Proposition 8:* There is a negative relationship between the broad-based, long-term use of an intelligent decision aid in a problem domain and the growth in knowledge and advancement of the domain.

In simple terms, Arnold and Sutton (1998) describe the roots of deskilling with the example of a situation where a knowledge worker approaches a task with the use of an intelligent system, whereas their predecessors had previously performed the task manually. The user simply enters information into the system and the system provides a recommendation (but also consider that the data could be automatically gathered and the user just reviews the recommendation). Will the novice user develop the knowledge of how to perform the task themselves as their predecessors did? Will an expert user who had the knowledge to perform the task themselves before using the aid, retain their knowledge if the system provides an extended skill layoff?

Research on TTD has established two ways that deskilling occurs: (1) skilled individuals/experts suffer an atrophy of skill and knowledge over time from use and reliance on intelligent systems, or (2) novice professionals do the same work traditionally leading to expertise development, but the inhibiting nature of the intelligent system limits individuals' expertise development. These aspects of the theory have held well when they have been tested with the effect on novices getting more attention. The atrophy of experts is more challenging to study due to the time elapse between first use of the system and extended use of the system—between the presence and the loss of knowledge. The Rinta-Kahila (2018; Rinta-Kahila et al., 2018) study captures this type of temporal effect as they observe knowledge workers in corporate finance performing a high-level task until the organization implements a system that takes over most of the work. Subsequently, the system was discontinued, and the same knowledge workers were unable to step in and complete the process themselves without the system's assistance. Their domain knowledge atrophied to the point they were at the level of advanced novices when they stepped back into the role.

There is more evidence on the novice development-side, although it is difficult to observe and capture. McCall et al (2008) used a short-term experiment to educate one set of management accountants with a computerized knowledge management system that provided easy access to information while another set learned through traditional searching of print materials. During interim projects, the knowledge management group performed better, but when both groups were tested after several weeks without access to any external materials, the knowledge management system group had significantly less knowledge retention and worse performance. A study of audit professionals by Dowling et al. (2008) provides a longer-term perspective. The researchers took data from a multi-firm experiment where audit seniors were identifying audit risk factors through manual processes and overlaid the performance with whether their firms had used highly restrictive or less restrictive audit support systems. Those audit seniors coming from firms that had used highly restrictive systems during their years of experience performed significantly worse on the risk assessment task than those from firms with less restrictive systems. Axelsen (2014) provides additional qualitative evidence for this finding through interviews with senior auditors who noted that novices who were rising through the ranks had a declining knowledge base. While the process level data is limited, Dowling and Leech (2014) note that novices have a mis-calibrated belief in what they know because of what they could do while using the support system. More experienced auditors expressed skepticism of the novices' ability to perform without the system. Perhaps even more concerning is Stensjö's (2020) findings that novice auditors readily admitted they did not really understand what they were doing while using the support systems. Cumulatively, the evidence supports the deskilling concerns that have been theorized.

Proposition #8 is even more difficult to empirically examine than the deskilling posited in Proposition #7. How does one know when a field's epistemology has stagnated? Recent research on technology and professions provides conceptual insights that may improve our theoretical understanding in this area. We explore related literature and its implications for the proposition.

5.1 The Skilling and Deskilling of Knowledge Workers

Varying paradigms examining expertise converge on the idea that expertise is essentially the possession of deep, structural knowledge of systematic relational patterns (e.g, Chi & VanLehn, 2012; Holyoak, 2012; Goldwater & Schalk, 2016).[5] The development of expertise, accordingly, entails an on-going process of encoding these relational patterns into memory to facilitate pattern recognition when stimuli are received in future instances. The Naturalistic Decision Making paradigm, for example, includes the Recognition Primed Decision model which posits that experts recognize patterns of cues

[5] In most domains, particularly those not involving muscle memory, thinking of expertise as a dichotomy is not helpful. Expertise is better construed as the acquisition, and appropriate structuring, of a significant amount of domain related knowledge, the development of which can be thought of as moving along a continuum. In this sense, significant knowledge acquisition can be construed as enough to understand how most of the components of a domain are related to one another. In professional domains, there are no appropriate binary classification as expert/non-expert. Some professionals are more expert than others in that they can better recognize patterns, based on inputs, and recognize the corresponding actions required considering those patterns.

based on having those patterns stored in memory and encode ‘solutions’ attached to specific situational patterns. Thus, the path to expertise includes acquiring a significant repertoire of knowledge composed of patterns comprising domain tasks (problems) and associated solutions. Research on analogical reasoning, a specific manifestation of relational reasoning, posits that these patterns are derived by professionals abstracting representations of structural knowledge that are separated from, or devoid of, surface level knowledge specific to particular occurrences within the decision domain (Gentner & Colhoun, 2010; Holyoak, 2012).

Traditionally, professionals acquire knowledge through focused experience and training. In professional firms, this training may consist of formal instruction or informal mentoring. Given enough time, professionals can learn implicitly (i.e., simply by doing) even when not actively trying to learn. However, as task domains become more complex, encoding the structural knowledge into long-term memory becomes more difficult—and less likely via implicit learning alone. This process can be enhanced by training that emphasizes conveying expert knowledge to non-experts as well as metacognition.[6] An emphasis on production efficiency rarely leads to system design that emphasizes features that facilitate user knowledge acquisition, nor are knowledge workers incentivized to acquire knowledge beyond that needed to complete the immediate task.

System design includes not only the creation of individual software systems, such as intelligent systems, but also overall work process systems created to guide task completion. Modern sociotechnical work environments involve division of labor into pieces of tasks as well as automation of subtasks. The result is distributed knowledge environments (DKEs). A DKE consists of all the knowledge required for completing a domain task being divided amongst multiple entities, which may be human, machine, or simply repositories. Professional firm innovations in both tangible and methodological technology continue to provide innovative ways of distributing knowledge among multiple people as well as multiple sources external to the human, such as document depositories, websites, and machines (Oshri et al., 2008; Simeonova, 2018). Additionally, many

[6] The importance of metacognition to expertise development is widely agreed upon (see for example Sternberg, 1998; Schraw, 2006; Klein, 1997; Fletcher and Wind, 2014). There is some precedent demonstrating the effectiveness of metacognitive training in a professional setting (e.g., Plumlee, Rixom, and Rosman, 2015). However, identifying further types of metacognitive skill and examining their relative impacts on knowledge acquisition is an area that requires additional research in professional domains.

subprocesses involved in professional decision making may be automated in order to bypass human cognitive capacity limitations as well as promote consistency and efficiency. Thus, in the normal course of the work process, any person involved in task completion is heavily reliant on other people and tools in accomplishing the task (Oshri et al., 2008; Simeonova, 2018). How do new 'experts' develop full knowledge structures when no one individual has a complete understanding of all aspects of the DKE?

This increasing distribution of task knowledge seemingly make processes more vulnerable to decision error and individuals more susceptible to deskilling. As processes become more complex and the requisite knowledge becomes more distributed, the proportion of the total required task knowledge understood by any individual will shrink, making it difficult for rising professionals to learn the entire systematic pattern of relational knowledge that makes up the overall domain (or big picture). This leads not only to process errors at the micro-level but also to deskilling of high expertise professionals at the macro-level. This exacerbates the aforementioned issues with TMS.

A common finding in research on relational reasoning is the tendency for novices to encode superficial problem features (specific to the current situation, which may not appear in similar future situations), which distract from encoding deep structural patterns (Day and Goldstone, 2012). The distribution of task knowledge may draw focus away from important structural relations, thereby exacerbating this tendency. This hinders pattern-recognition if the subsequent cues do not include the superficial knowledge, and ultimately system users' ability to acquire knowledge from experience. Participants in DKEs, by design, will not possess the requisite knowledge to complete a task. Thus, the patterns comprising the subset of knowledge that they are supposed to possess will likely not be encoded properly to long-term memory—which is associative by nature. Missing pieces of the structural knowledge in memory can lead to pattern-recognition failures when encountering certain subsets of cues or when observing relational patterns in even slightly different contexts. Problems with DKEs can also be exacerbated by any automated portions completed entirely by an intelligent system that are not designed to convey relational knowledge to professional decision-makers. Failure to convey system logic, and how it relates to the task as a whole, makes even implicit learning very challenging.

As also noted earlier, professionals operate amidst several system influences enabling the lack of skill development. Novice decision-makers in professional environments are increasingly provided systems to supplement their work that include easy search and retrieval of performance guidance and AI-components that facilitate task completion with limited user involvement. Given an innate orientation for quick task completion without deep exploration of the problem, novices let technology lead task completion—essentially a TMS strategy but with a system that does not require the user to participate in reciprocal knowledge sharing. Novices feel satisfaction from "having made the decision" and in the process become mis-calibrated in assessing their own knowledge, developing overconfidence in their abilities (Fisher et al., 2015). This "react fast, make a decision, and move on" unconsciously promotes shallow decision-making that does not trigger deep-thinking or the encoding of deep knowledge structures into long-term memory (Loh and Kanai, 2015). This setting provides little motivation or desire to enhance knowledge acquisition, resulting in a failure to facilitate active learning and a lack of expertise development over time.

We posit that failure to learn the relational knowledge of a domain results in a lack of encoding of relational knowledge in long-term memory, which is at the heart of deskilling. This can also result from experienced practitioners having skill-layoffs in which they are not recalling and activating knowledge for extended periods of time. As noted in the prior section, experts are expected to maintain their expertise development under collaborative system relationships that allow them to share knowledge and explore tasks at greater depth (Arnold and Sutton, 1998). Deskilling of experts is expected to arise through the nature of adaptive automation allowing experts to decide not to exert decision control but rather to simply rely on trusted systems (Hancock, 2014). Related to the autonomous systems issue, deskilling also arises from simply automating a process and removing the experts from decision-making (Rinta-Kahila et al., 2018). Both result in extended skill-layoff, which leads to skill atrophy and diminished underlying knowledge structures. Professional firms increasingly deploy intelligent systems that incorporate such effort-reducing strategies for efficiency gains (Susskind and Susskind, 2015).

The above leads to the following propositions:

> *Proposition 7a:* The more that intelligent systems allow novices to focus purely on production activities, the poorer the knowledge structures that will be developed by the user.
>
> *Proposition 7b:* The more that intelligent systems allow experts to have skill-layoffs, the greater the likelihood of attrition of the user's expertise.

> *Proposition 7c:* The less transparent that an intelligent system is in providing an expert with an understanding of how information is used in a decision and how decisions are formulated, the greater the risk of deskilling the user.
>
> *Proposition 7d:* The more that intelligent systems are designed to communicate structural pattern data to novice users, the better the knowledge structures that will be developed by the user.
>
> *Proposition 7e:* The use of unexplainable artificial intelligence techniques in intelligent systems supporting experts will increase the risk of deskilling the user.

Propositions 7c and 7e are of significant concern to decision-makers across a range of knowledge work environments. Proposition 7c deals with the more general case of transparency of system processes, while Proposition 7e is the extreme case of transparency not being possible (unexplainable artificial intelligence (AI)). Militaries have been particularly concerned with the risk of acting upon warnings from unexplainable AI, and DARPA's most recent round of challenge awards are for the design of explainable AI techniques that are equally powerful to the best unexplainable AI techniques (Sutton et al., 2018). This transparency issue has also drawn attention from the professions, where for instance audit researchers working on AI for audit data analytics, recognize the concerns of not being able to explain their decisions (Zhang et al., 2021). Organizational forces may envelop the AI techniques to control the unknown (Asatiani et al., 2021), but the unknown invariably limits experts' reliance.

We have a limited understanding of how knowledge of important structural patterns can be transferred/presented to users, but research has begun to explore system designs that may help. Rose et al. (2007) introduced building knowledge maps into system interfaces with some success, and this was expanded upon by Arnold et al. (2022) which used more complex knowledge structures and coupled the knowledge structures with automatic explanation provision (Arnold et al., 2006). Researchers should continue to focus on methods of system design, both at the macro (DKE) and micro (intelligent system) levels that allow and encourage user knowledge acquisition. However, the goal here is not just to make implicit learning easier, but to facilitate the active learning of deep domain knowledge. Therefore, researchers should also seek methods of effectively training novice professionals in metacognitive strategies that focus on acquiring deep structural knowledge (e.g., relational reasoning).

5.2 Epistemological Stagnation?

For purposes of TTD, epistemology is defined as "having to do with the origin, nature, methods, evolution and limits of human knowledge" (Sutton and Byington, 1993). The epistemology of virtually every knowledge work profession has evolved tremendously over the past several decades. Epistemological evolution is fueled by the sharing of ideas across numerous experts, particularly during periods of high growth, breeding new advances in domain knowledge (Arnold and Sutton, 1998). TTD raises the concern that the broad implementation of intelligent systems in a domain limits diversity of thought as an increasing number of experts are either learning from the same myopic system or perhaps being deskilled by those systems. Does the variety and discourse over knowledge decline? This is captured in TTD's Proposition #8.

The epistemological stagnation debate has taken on a more sobering dimension in recent philosophical discourse. The professions that have for so long held a significant role in western society are considered under attack (Callahan, 2007; Susskind and Susskind, 2015). These professions have held their stature based on a recognized specialized knowledge, certification and licensing processes, codes of professional conduct, and societal trust and reputation (Kultgen, 1988; Susskind and Susskind, 2015). But increasingly the work that professions provide is being automated through technology (Susskind and Susskind, 2015). This is shaking the professional domains of auditing, law, medicine, and tax compliance and planning. But beyond these external pressures, we also see professions internally adopting automated technologies that displace the human knowledge worker (Sutton et al., 2018; Strich et al., 2021). Increasingly, the automated processes that are being adopted and integrated generally either simplify and structure work processes (Dowling and Leech, 2014) or simply displace work routines with AI (Strich et al., 2021; Zhang et al., 2021). Almost all the intelligent systems implemented in the professional domains automate current work, they do not evolve the epistemology (Susskind and Susskind, 2015). With this automation, one may ask, Where will the epistemological growth come from? (Arnold and Sutton, 1998). Will the professionals remain associated with the profession? When displaced by technology, may the experts just move on to some other professional domain? (Strich et al., 2021).

The counter argument to these concerns is that automation of the professions is positive for society as a whole. Susskind and Susskind (2015) argue that using automation to make professional services more accessible to more people, by-passing professional firms who limit accessibility to their services, means more people/companies have affordable access. Rather, disruptive technologies demystify the work of the professions, routinizing professional work, and making it more accessible—being disruptive only to the professionals (Susskind and Susskind (2015). This has commonalities to the arguments presented by Stricht et al. (2021) as to the displacement of professionals by automation and lends itself to the paraprofessional model where lesser expert knowledge-work professionals can take the lead when armed with intelligent systems (Susskind and Susskind, 2015; Sutton et al., 2018). Susskind and Susskind (2015) argue we are entering a post-professional society, a deprofessionalization of knowledge work done by the professions.

Within the information systems research community, there is much debate over the roles of design science and behavioral science paradigms (Sutton et al., 2021). Within the design science side, the focus recently has been on the importance of design science research producing new artefacts and in most cases *design theory* (Baskerville et al., 2018). Design theory can either be the subject of the artefact instantiation or what is learned from the instantiation. In essence, design theory provides prescriptions for design, but design theory also says how to do something (Gregor and Hevner, 2013). Given the radical changes in professions that we are seeing through new technologies, one should consider that the advances in a field may come from what we learn through designing or applying novel technologies rather than what a profession demands is incorporated in the technology. Arguably, this is emblematic of what is happening with the audit profession now as novel AI techniques alter the way auditing is performed. Similarly, in medicine AI systems are being used to seek patterns in medical research findings and to generate new relationships and medical solutions to long-time problems (Susskind and Susskind, 2015). The hesitancy from the professions comes largely from not knowing what those technologies are doing (Sutton et al., 2018; Asatiani et al., 2021; Zhang et al., 2021).

Based on these varied perspectives on the evolution of professions, we propose several alternative ways of thinking about epistemological evolution in professional knowledge work environments.

Proposition 8a: Human discourse on improvement and evolution of a profession will stagnate in the presence of prolonged use of intelligent systems.

Proposition 8b: The more predominant intelligent systems become in a profession, the greater the deprofessionalization of that profession.

Proposition 8c: Use of intelligent systems in a profession may trigger epistemological change through advances in design theory and innovative techniques.

6.0 CONCLUSIONS AND IMPLICATIONS FOR FUTURE RESEARCH

There is an increasing recognition that something about technology makes people less skilled. This has raised discussions on how we make intelligent systems beneficial to the user, not just for work productivity, but also to maintain skilled knowledge workers (Sutton et al., 2016, 2018; Balasubramanian et al., 2017; Asiatani et al., 2019). Strategies have been put forth to start thinking about how we keep the human relevant. In this expansion of TTD, we focus on the underlying cognitive processes that appear to lead to poorer decision making, inattentive expert decision-makers, and deskilled knowledge workers. TTD2 is founded on a synthesis of studies from many domains, including accounting, psychology, human factors/ergonomics, neuroscience, and information systems. The result is a set of propositions that should be scrutinized, tested, and expanded upon.

While much empirical evidence supports the existence of technology dominance and related components such as automation bias, complacency, and ineffective transactive memory systems, much is left to consider in trying to understand how technology dominance occurs. In formulating TTD2, substantial reliance has been placed on two parallel streams of research, but these proposed behavioral theory extensions should be carefully examined in future research. The work on automation bias and complacency has evolved from automated decision aids and how monitoring systems that alert the user can induce overreliance. TTD2 considers this in the context of interactive decision aids that support knowledge workers' decision-making, but it needs to be empirically considered whether these effects translate to this intelligent systems domain. Similarly, the research on transactive memory systems and the so-called Google Effect has essentially all been completed with a focus on Internet search behavior and execution. TTD2 translates this to intelligent systems that are designed to support knowledge workers given the embedded search functions that readily identify facts, definitions, and work process recommendations. This extrapolation similarly will benefit from empirical examination. Other effects will likely arise during these examinations.

While TTD2 is a theory of behavior and the underlying cognitive processes, it is critical that it is also viewed as a foundation for design science research (Hevner et al., 2004; Sutton et al., 2021). Advances in intelligent systems design have come from leveraging the synergies of behavioral and design science research (Sutton et al., 2021). Without the design science part of the equation, it will be challenging to move the concepts articulated in TTD2 to a meaningful and practical implementation in contemporary systems. TTD2 posits the benefits of systems that provide enhanced transparency on how decision processes and decision outcomes are produced by an intelligent system, but contemporary designs are not necessarily effective at providing this transparency (Gregor and Benbasat, 1999; Arnold et al., 2006; Jensen et al., 2010). At the extreme, users are reluctant to rely on highly effective AI techniques when they are unexplainable, leading to the call for improved explainable AI algorithms (Sutton et al., 2018; Zhang et al., 2021). Further, designs that promote pattern recognition as a foundation for effectively promoting expertise development among novices have had limited success, and new techniques should be explored (Sutton et al., 2022). Finally, the focus on adaptable systems that allow experts to determine when they want to participate in the decision-making process appear to deskill these experts with skill layoffs; and, the way such systems are designed should be reconsidered for whether this concept can be effectively implemented without deskilling the users (Parasuraman and Wickens, 2008; Hancock, 2014).

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