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Extending March's Exploration and Exploitation: Managing Knowledge in Turbulent Environments

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Abstract

We extend March's model of exploration and exploitation to consider how environmental turbulence impacts organizational knowledge in hierarchies of varying size and depth. We then evaluate additional effects of a knowledge management (KM) system that collects and shares knowledge from expert individuals in an organization. We find that in the absence of personnel turnover, a management strategy of high exploitation and low exploration for a multi-tier hierarchical organization, representative of a "top-down" knowledge management strategy, reduces the accuracy of average individual knowledge levels compared to alternative strategies. The magnitude of this reduction in accuracy increases as the number of tiers in a hierarchical organization increase. Managers operating in a flat organization will see less of a reduction compared to a multi-tier organization. Two weighted-least-squares regressions performed on two additional data sets corroborate this central observation: a "bottom-up" strategy demonstrates greater resiliency to environmental turbulence than a "top-down" knowledge management strategy for hierarchical organizations.

Keywords: knowledge-based theory of the firm, knowledge management strategy, environmental turbulence, exploitation, exploration, turnover, flow, bottom-up, top-down

Introduction

According to the *knowledge-based theory of the firm*, knowledge represents the most strategically valuable resource of any organization (Grant 1996; Argote and Ingram 2000). Knowledge exchanges allow humans to become more "fit" to their environment, by either engaging more effective or more efficient choices in the context of specific environmental events (Nonaka 1994; Markus 2001). Information technology serves a critical enabler underlying such knowledge exchanges (Drucker, 1988; Alavi and Leidner 2001). We define a critical component of a *knowledge management strategy* as the representation of an organizational goal and the coordination of routines that facilitate the dissemination and interpretation of relevant knowledge such that the organization's approximation of reality sufficiently matches external reality (Heckscher and Donnellson 1994; Clippinger 1999; Bray 2007). However, knowledge can be time sensitive, potentially losing its relevance as environments change (Galbraith 1982). For a knowledge management strategy to succeed, capturing and sharing knowledge of expert and innovative employees may provide a strategic advantage positively influencing performance outcomes if and only if the knowledge collected and disseminate accurately matches external reality.

That said, in order for distributed, heterogeneous knowledge bases to be intentionally leveraged as a strategic asset, managers not only need to identify what employees know (and do not know) to appropriately target the transfer of knowledge, but also need to discern when such knowledge will be valuable both now and in the future (Eisenhardt 1989; Cummings 2004; Andrus 2005). Consequentially, unless managers assume omniscience, it may be nearly impossible to discern in advance the knowledge currently known and not known by employees, what knowledge is worth capturing for both present and future reuse, when such reuse will be appropriate, and when creating entirely new knowledge will be required (Anderson 1999; Marjchrzak et al. 2007).

With globalization, managers increasingly coordinate groups of globally distributed individuals who must exchange time-sensitive knowledge relevant to successful outcomes (Weick and Roberts 1993; Darr et al. 1995; Levin and Cross 2004). In such settings, knowledge known today may lose its relevance in the future due to environmental changes (Winograd and Flores 1987; Carley and Lin 1997; Markus 2001). These challenges impede the success of any knowledge management strategy, particularly when confronted with *environmental turbulence*, defined as sudden, stochastic changes to external reality that invalidate aspects of organizational knowledge relevance or effectiveness (March 1991; Siggelkow and Rivkin 2005). For modern organizations, often no single individual harbors sufficient knowledge to either mitigate negative outcomes or capitalize on positive opportunities, and interindividual exchanges must transcend physical group proximity and social networks (Galbraith 1982; Huber 1990; Uzzi 2003; Singh 2005). When faced with turbulent environments, managers may not capably discern what knowledge is valuable to keep pace with changing demands, as they, like all employees, are boundedly rational social beings – a central tenet embodied in modern research theories describing how organizations learn (Levitt and March 1988; Simon 1992; March and Simon 1993).

Hierarchical management structures, despite their imperfections, are remarkably ubiquitous in organizations (Leavitt 2005). Building upon existing research, we postulate that such attempts at top-down "management" of knowledge may be infeasible if turbulent events prove too dynamic for managers to forecast environmental changes and organizational demands reliably (Anderson 1999; Clippinger 1999; Marjchrzak et al. 2007). To test this postulate, we extend March's (1991) research to consider exploration and exploitation in a hierarchical organization experiencing environmental turbulence. To provide a comprehensive comparison, we compare different knowledge management strategies while maintaining equally turbulent environments, keeping other variables constant.

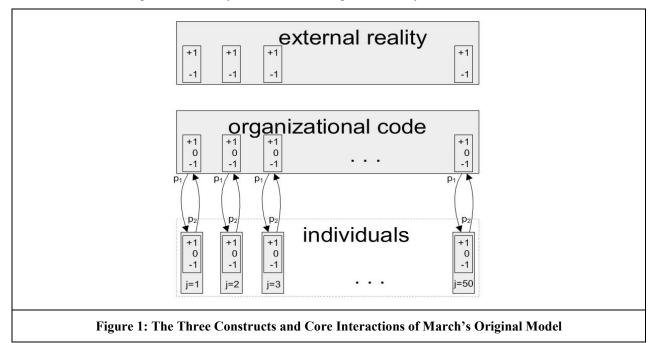
From the perspective of established knowledge management systems literature, we define knowledge as "justified belief that increases an entity's capacity for effective action" and intend to examine how knowledge transfer is achieved in an organization through its formal hierarchy and, in select instances, through a knowledge management system (Alavi and Leidner 2001). We link this examination of knowledge transfer to organizational learning literature, which examines the mutual learning of an organization and the individuals in it (March 1991; Alavi and Leidner 2001). In the next section, we highlight important elements of March's (1991) original model of exploration and exploitation, with the goal of extending his theoretical model to consider knowledge management strategies within a hierarchical organization experiencing environmental turbulence. We offer (and test computationally) four hypotheses related to our extension of March's (1991) seminal model.

Theoretical Model

March's (1991) Original Model

James G. March conceived a model of organizational learning as a balance between the exploration of new alternatives and the exploitation of existing competencies in an organization (March 1991). His original model is succinct and abstract, comprising an external reality, individual knowledge about external reality, and an organizational code representing an approximation of external reality derived from the individuals' knowledge. Literature surrounding this model is extensive, examining theoretical extensions as well as empirical support (e.g., Benner and Tushman 2003, Lee et al. 2003; Kane and Alavi 2005; Jansen et al. 2006). For this study, extending March's original model to consider different knowledge management strategies for a multi-tier hierarchical organization is ideal, since we can employ his established research model to consider how knowledge transfer (embodied in March's model of organizational learning) is achieved in an organization through its formal hierarchy and through a knowledge management system. Echoing March (1991), knowledge is interpreted to be an abstract and complex construct that subsumes a variety of instantiations potentially influencing organizational decisions, to include "procedures, norms, rules, and forms" (p. 73, March 1991).

In brief, March's original model circumscribes external reality as a vector of m = 30 integers (either -1 or +1), each representing an independent dimension of reality. Individual knowledge comprises a similar vector of 30 integers, with the allowance of a value of zero for an independent dimension, representing no belief. Organizational code is a similar vector of 30 integers. March considers external reality as constant and defines an abstract organization to consist of n = 50 individuals (see Figure 1). March finds that the qualitative results of the model are insensitive to values of *m* and *n*. This premise similarly holds for the findings of this study.



March defines an individual knowledge level as the proportion of external reality correctly represented by an individual knowledge vector. Separately, the proportion of reality correctly represented by the organizational code defines an organizational knowledge level. There is only one organizational code, hence only one organizational knowledge level. Both individual and organizational knowledge levels potentially change via organizational learning, represented as two distinct interactions among the 50 individuals and an overarching organizational code. For each iteration of the model, every individual has the potential to change any belief to conform to the corresponding knowledge of the organizational code with a probability p1 representing the probability of an organization to influence individuals' knowledge – *exploitation*. This approximation of exploitative behavior serves

to model individual learning from the organizational code. Equally, for each iteration, the organizational code has the potential to alter any belief to match the knowledge of the most accurate (i.e, expert) individuals with a probability p^2 representing the probability of an organization to alter its presumed view of reality – *exploration*. This approximation of explorative behavior serves to model organizational learning from experts (see Figure 1).

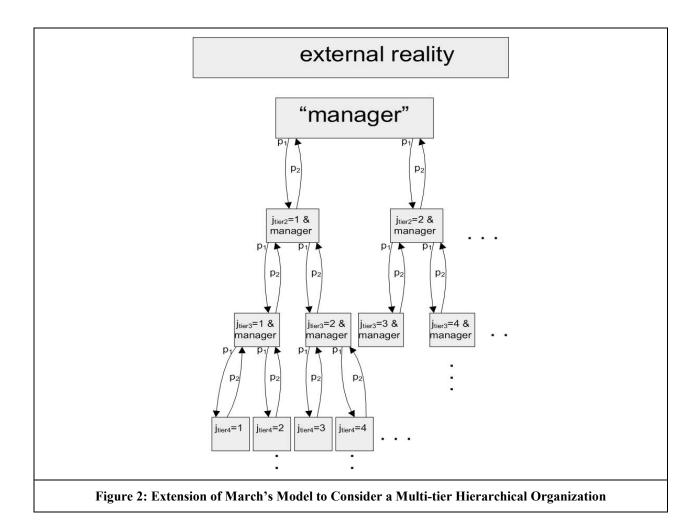
March expands his formative model to consider a more open system, comprising personnel *turnover* and *environmental turbulence*. For each iteration, every individual has the potential to leave an organization and be replaced by a new individual, with a probability p3 reflecting this personnel turnover. New individuals enter with randomly distributed beliefs. Additionally, every dimension of external reality has the potential to flip, with a probability p4 reflecting external environmental turbulence. March's model intentionally precludes both individuals and an organization from directly observing external reality. Instead, improvement in individual and organizational knowledge levels comes either from the organizational code adapting to the knowledge of expert individuals or from individuals by their overall individual knowledge levels, and cannot pinpoint which specific beliefs are true or false for a given dimension of reality.

Extending the Original Model

Our first extension to March's model examines the effect of additional tiers in a hierarchical organization. The original model considers all individuals as peers, and hence represents a flat organizational structure. An extension positions a single manager at the top tier in the hierarchical organization with a set of direct reports. This manager corresponds to the organizational code in March's reality. Multiple organizational codes exist as different tiers in the proposed hierarchical organization with each direct report, in turn, a manager for another set of direct reports recursively until reaching the bottom tier. Individuals at the bottom tier have no direct reports. The hierarchical organization consists of d tiers, where d is an integer between 2 and 5 (see Figure 2). In this first extension, each individual retains the potential to conform to the beliefs of their supervising manager (p1) and each manager retains the potential to alter a belief to match the dominant knowledge of expert direct reports (p2). This extension preserves the concepts of personnel turnover (p3) and environmental turbulence (p4). The dominantly held views for a specific period of time now define the knowledge equilibrium of a multi-tier hierarchical organization.

Such an extension to the model is simple, intuitive, and with precedent. While in reality, human individuals in an organization learn from several influences, with this study we examine the specific effect of a "manager" on their reports – and reports on their "manager" – so that our results can clearly demonstrate the influence of each. We also seek to maintain the original parsimony of March's original model. Learning in multi-tier hierarchical organizations has been considered in other models (Carley 1992; Carley and Lin 1997; Rivkin and Siggelkow 2003; Kane and Alavi 2005), but no published research to date has expressly advanced March's seminal model for such purposes, and few have considered the effect of environmental turbulence. Kane and Prietula (2003) did make an extension to March's model for a two-tier hierarchy and found that as the span of the lower level (i.e., size of managed groups) increased, it became more difficult for the organizational code to adopt accurate exploration results and hierarchical organizations comprised of rapid learners substantially underperformed those comprised of slow learners. Yet their research did not consider a multi-tier hierarchical organization, nor did their model include the effects of personnel turnover and environmental turbulence (Kane and Prietula 2003). Our proposed extension has the advantage of allowing for initial validation and subsequent extension of all constructs contained in March's model (Burton and Obel 1995).

Our second extension to March's model examines the effect of a knowledge management system collecting knowledge from a set ratio of experts. With this extension, the knowledge *flow* and the connections between individuals define an organization's structure and managerial relationships (Galbraith 1982; Lin and Hui 1997; Heckscher and Donnellson 1994). Individual users are social actors who interact with information systems, both influencing and influenced by social dimensions of these interactions (Lamb and Kling 2003; Cummings 2004). Inherent to the structure of a multi-tier hierarchical organization is that individuals report to different managers, potentially producing fragmented connections in terms of the flow of information and organizational learning (Mayer and Gavin 2005; Singh 2005). In this second extension, fragmented connections can be predicted to introduce a knowledge flow delay in an organization, where the time (i.e., number of iterations) required for individual knowledge levels in an organization to reach a stable knowledge equilibrium increases as the number of tiers (d) in the hierarchical organization increases (Schulz 2001; Benner and Tushman 2003).



In terms of cumulative research value, hierarchies remain the basic structure of most large, ongoing human organizations (Jaques 1990; Leavitt 2003). Similarly, established research shows that collecting and sharing expert knowledge can produce a long-term competitive advantage for an organization (Nonaka 1994; Alavi and Leidner 2001; Tsai 2001; Lee and Choi 2003). Recent research has conceptualized varying organizational structures as different networks of social individuals whose position in the network can influence knowledge transfer and organizational learning (Lee, Lee, and Lee 2003; Hansen, Mors, Løvås 2005; Inkpen and Tsang 2005). By extending March's stylized model to account for a hierarchical organization, the effect of additional tiers in a hierarchical organization can be tested and linked to March's original constructs of exploration, exploitation, personnel turnover, and environmental turbulence.

For the purposes of examining which strategy is better, exploration in a hierarchy represents an increased probability of managers incorporating the knowledge of their reports. Consequentially, this explorative knowledge flow starts at the bottom and moves up in a hierarchy, representative of a *bottom-up* knowledge management strategy (Galbraith 1982; Clippinger 1999). Exploitation represents an increased probability of reports incorporating the knowledge from their reports. This exploitive knowledge flow starts at the top and moves down in a hierarchy, representative of a *top-down* knowledge management strategy (Heckscher and Donnellson 1994). Additionally, this study affords for systematic examination of two dimensions of a knowledge management system: (1) the effect of increasing or decreasing the collective probability of norms of use and influence of a knowledge management system that embeds lagged but accepted organizational procedures, and (2) the effect of collecting knowledge (as beliefs of reality) from a wider or narrower ratio of expert individuals.

Methods and Hypotheses

Our first experiment serves to verify that our simulation and two extensions preserve the integrity of March's original model. All parameter values selected are consistent with March's original values. We wrote a computer simulation to perform our experiments using Microsoft Visual Studio .NET.

Our second experiment evaluates the effect of varying the number of tiers in a hierarchy (d, from 2 to 5) on the accuracy of average individual knowledge levels with external reality (i.e., the outcome variable of interest). This second investigation retains March's original constructs of exploitation (p1), exploration (p2), personnel turnover (p3), and environmental turbulence (p4) as defined earlier. For this second experiment, we hypothesize, *ceteris paribas*:

H1: Additional tiers in a hierarchy will decrease the accuracy of average individual knowledge levels when an organization opts for a strategy of high exploitation and low exploration in a multi-tier hierarchical organization.

H2a: Increasing personnel turnover (within the values of 0.000 to 0.040) will increase the accuracy of average individual knowledge levels in a multi-tier hierarchical organization.

H2b: Increasing environmental turbulence (within the values of 0.000 to 0.040) will decrease the accuracy of average individual knowledge levels in a multi-tier hierarchical organization.

Justification for our first hypothesis (H1) is that a strategy of high exploitation gives more credence to the knowledge of the manager over the subordinates (even if subordinates have expert views), and thus places a substantial weight on organizational position over expertise. In contrast, a strategy of high exploration does consider the knowledge of the top experts (over less knowledgeable individuals) reporting to the manager when influencing the manager's beliefs. Thus, as the number of tiers in a hierarchical organization increase, a bottom-up strategy (i.e., exploration in the hierarchy) will continue to consider the expertise of subordinates reporting to managers, of which there will be an ever-growing number, while a top-down approach will continue to place weight on the knowledge of managers based on their height within the hierarchy. Given these two different approaches, a bottom-up approach should more adopt accurate knowledge dispersed throughout the organization as compared to a top-down approach (Clippinger 1999). Research regarding complex adaptive systems generally supports the value of a bottom-up strategy in helping systems adapt to turbulent environments, and this study hopes to provide similar evidence with regard to knowledge management strategies (Anderson 1999; Andrus 2005; Bray 2007; Marjchrzak et al. 2007).

Our justification for the additional two hypotheses (H2a and H2b) stems from research indicating that multi-tier hierarchies are structures built to maintain a sense of order and a set of internal knowledge (Leavitt 2003). Since multi-tier hierarchies tend to sustain a set of internal beliefs, changing internal beliefs to match changes in external reality can be problematic. In the face of environmental turbulence, multi-tier hierarchical organizations cannot adapt as quickly as flat organizations. However, personnel turnover is an exogenous factor that (potentially) introduces diverse beliefs about external reality into an organization, as March (1991) similarly finds. These diverse beliefs both functionally (and stochastically) expand the search space of knowledge within the organization.

Our third experiment evaluates the effect of increasing or decreasing the collective probability of norms of use and influence of a knowledge management system (pKM) and the effect of collecting knowledge, as beliefs from wider or narrower ratios of expert individuals (rEX) on the average knowledge equilibrium. This third experiment considers a knowledge management system as a globally accessible organizational code containing the consensus of a number of expert individuals in the organization. Such an approach mirrors (in a flat organization) March's single organization code from which all individuals can potentially learn from (i.e., pKM for a flat organization is analogous to pI, exploitation, in March 1991). For this third experiment, we hypothesize:

H3: Increasing the probability of norms of use and influence of a knowledge management system (pKM) will increase the accuracy of average individual knowledge levels, insomuch that the knowledge management system does not become another source of exploitation (i.e., beyond an inflection point, increasing the probability of norms of use and influence of a knowledge management system will decrease the accuracy of average individual knowledge levels).

H4: Widening the number ratio of expert individuals (rEX) whose consensual knowledge is included in the knowledge management will introduce additional randomness into the system and decrease the accuracy of average individual knowledge levels.

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Our justification for these two hypotheses is that if a knowledge management system is similar to an organizational code – in its ability to facilitate knowledge transfer to all members of the organization – then pKM (the probability any one individual may learn from the knowledge management system) is analogous to exploitation pressures. As such, it follows that beyond a certain point additional use of a knowledge management system will hurt an organization rather than help it (Levine and Prietula 2006). Similarly, if the value of a knowledge management system is in its ability to provide expert knowledge to all members of the organization, widening the definition of expert individuals (*rEX*) to include more individuals in the organization with "less expert" opinions will decrease the value of a knowledge management system (Leavitt 2003; Leavitt 2005). We predict that a knowledge management system that simply provides the consensus of all individuals in an organization does not identify any specific experts and consequentially will not improve organizational performance.

Our fourth experiment performs two regressions on two additional sets of sample data. With this experiment, we examine more thoroughly the second and third experiments by analyzing 6,000 random samples from the total population of all possible organizational strategies.

Results and Discussion

Experiment 1: validation against March's model

For the purposes of replication and validation of March's model, we generated a two-tier hierarchical organization. Our simulation includes the same number of agents and same vector sizes. The simulation ran for 200 iterations for three different values of individual learning (p1 = 0.1; 0.5; 0.9) and for three different values of organizational learning (p2 = 0.1; 0.5; 0.9), similar to the original model. The absence and presence of personnel turnover (p3 = 0.00; 0.02) was considered alongside the absence and presence of environmental turbulence (p4 = 0.00; 0.02). The first experiment performed 40 separate simulation runs to accommodate the stochastic properties of the original model. The qualitative results of this first experiment paralleled March's original observations: there is a central dichotomy between exploitative and explorative organizational learning strategies.

An exploitative strategy (p1) represents refinement of existing competencies in an organization, with predictable short-term returns. Conversely, an explorative strategy (p2) represents experimentation with new alternatives in an organization, with uncertain long-term returns. Though both strategies occur independently, finding an appropriate balance between the two is a primary factor in determining the accuracy of average individual knowledge levels with external reality. An organization with a misaligned exploitation and exploration knowledge management strategy will quickly lose its relevancy.

Further, under conditions of environmental turbulence (p4 = 0.02) with no personnel turnover (p3 = 0.00), the mutual learning between organizational and individual knowledge levels produces a long-term degenerative effect. Organizational and average individual knowledge levels converge to match each other, reducing the possibility for either to change to approximate external reality with greater accuracy. Once achieving knowledge equilibrium, the probability for either organizational or average individual knowledge levels to change becomes zero since all individuals now share the same exact beliefs. A modest level of personnel turnover avoids such knowledge degeneracy. Introducing a new individual exposes the organization to a set of naïve, non-conforming beliefs of reality. This provides potential opportunities for individuals in the organization to improve their knowledge levels.

Additionally, we repeated the first experiment with a larger number of individuals, as we eventually wanted to consider a hierarchy of about 136 individuals (compared to March's 50 agents). As March indicated in his paper, we also found our qualitative observations to remain unchanged with additional individuals.

Experiment 2: multi-tier hierarchies

Our second experiment evaluated the number of tiers (d) as an independent variable in tandem with the number of individuals reporting to a single manager (b). Four different hierarchical organizations were considered (d = 2 and b = 132; d = 3 and b = 11; d = 4 and b = 5; d = 5 and b = 3), each representing an organization with approximately 136 individuals. For example, a three-tier hierarchical organization with each manager having 11 direct reports represents 133 individuals in an organization. The size of hierarchical organization was held constant. Similar to March's model, initial belief values for individuals without any direct reports were randomly distributed (i.e., either

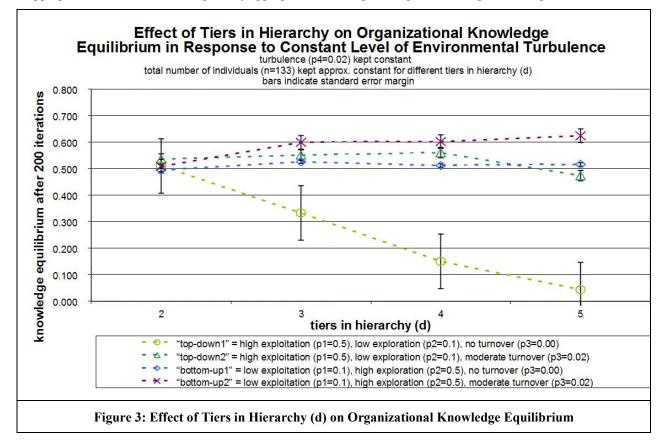
-1; 0; +1), whereas the belief values for managers (i.e., distinct organizational codes with direct reports) were all initially neutral (i.e., set to 0). Managers had the possibility of exploratory learning (p2) from an expert direct report with the highest number of beliefs matching that of external reality. In the event of tied experts, the managers randomly selected one of the top individuals. As before, 40 separate simulation runs were performed per treatment. Differences in the accuracy of average individual knowledge (Y) were assessed by analysis of variance (ANOVA).

Figure 3 broadly visualizes our findings, with the vertical bars representing standard errors for our experiment. For hierarchical organizations, a top-down knowledge management strategy (i.e., high exploitation with pl = 0.5, and low exploration with $p_2 = 0.1$) in the absence of no personnel turnover ($p_3 = 0.00$) reduced the accuracy of average individual knowledge levels with external reality the most compared to alternatives. Yet such a finding is statistically significant only when considering a top-down knowledge management strategy for a multi-tied hierarchical organization confronting environmental turbulence. March's original model did not observe such a finding since the model considered only a flat organization.

Specifically, for a flat organization (i.e., only one organizational code, d = 2) confronting environmental turbulence (p4 = 0.02), after 200 iterations we found no differences between a bottom-up or a top-down knowledge management strategy either in the absence or present of personnel turnover, as an ANOVA between groups revealed a p-value of 0.212 (i.e. greater than 0.05 and thus non-significant). However, with similarly turbulent environments, for a multi-tier hierarchical organization (d = 3, 4, or 5) and in the absence of personnel turnover, we did find significant differences between groups (individual ANOVA for three, four, and five tiers all revealed p-values < 0.0005). See Table 1 for details.

GROUPS		COUNT	SUM	AVERAGE	VARIANCE	CONSTANT
"top-down1", tiers = 2		40	20.431	0.511	0.013	environmental
"top-down2", tiers = 2		40	21.465	0.537	0.005	turbulence,
"bottom-up1", tiers = 2		40	19.836	0.496	0.006	p4 = 0.02
"bottom-up2", tiers = 2		40	20.368	0.509	0.007	
"top-down1", tiers = 2		40	13.328	0.333	0.007	
"top-down2", tiers = 3		40	22.069	0.552	0.006	
"bottom-up1", tiers = 3		40	21.069	0.527	0.011	
"bottom-up2", tiers = 3		40	23.999	0.600	0.008	
"top-down1", tiers = 4		40	6.032	0.151	0.005]
"top-down2", tiers = 4		40	22.432	0.561	0.010	
"bottom-up1", tiers = 4		40	20.500	0.513	0.014	
"bottom-up2", tiers = 4		40	24.100	0.603	0.006	
"top-down1", tiers = 5		40	1.763	0.044	0.001	
"top-down2", tiers = 5		40	18.966	0.474	0.006	
"bottom-up1", tiers = 5		40	20.667	0.517 0.625	0.007 0.008	
"bottom-up2", tiers = 5		40	24.998			
VARIATION	SS	Df	MS	F	P-VALUE	F-CRIT
Between Groups	15.634725	15	1.042315	140.22347	2.4501E-188	1.682432
Within Groups	4.638343	624	0.007433			
Total	20.273068	639				
"top-down1" = high	exploitation (p1=	0.5), low explo	oration, (p2=0.	1), no turnover	(p3=0.00), tiers	<u>;=4</u>
"top-down2" = high	exploitation (p1=	0.5), low explo	oration, (p2=0.	1), turnover (p3	=0.02), tiers=4	
•).5), no turnover		

Our results show that a strong top-down knowledge management strategy (i.e., high exploitation and low exploration) with no turnover significantly reduced the accuracy of average individual knowledge levels. Keeping all other variables constant, increasing the number of tiers in a hierarchical organization increases this reduction in accuracy. In the absence of personnel turnover, a five-tier hierarchical organization (d = 5) will see a greater reduction in accuracy from a top-down knowledge management strategy (i.e., high exploitation and low exploration) when compared to a three-tier hierarchical organization (d = 3) with approximately the same number of individuals employing the same strategy. Additional tiers in a hierarchy amplify the negative effect of this top-down knowledge management strategy in the absence of turnover. However, our results also illustrate that the negative impact of inappropriate structure can be mitigated by appropriate knowledge management strategies. See Figure 3 for details.



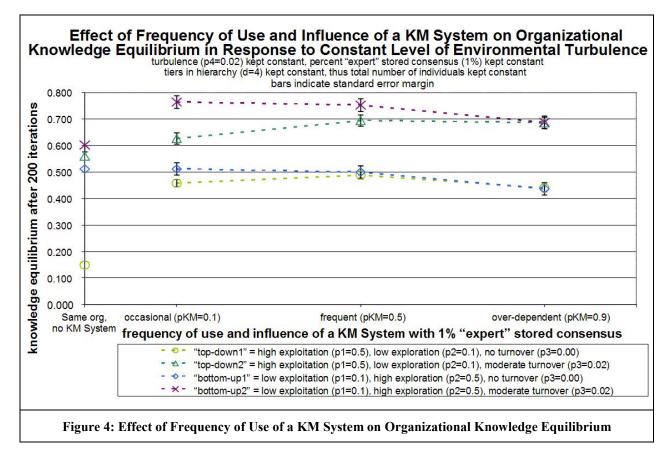
Experiment 3: incorporating a knowledge management system

Two variables were manipulated in this experiment: (1) the effect of increasing or decreasing the collective probability of norms of use and influence of a knowledge management system (*pKM*), and (2) the effect of collecting knowledge (as beliefs of reality) from a wider or narrower ratio of expert individuals (*rEX*). Three probabilities were used to describe the collective probability of norms of use and influence of a knowledge management system (*pKM* = 0.01; 0.05; 0.09). These values represented low, moderate, and high values and were similar both in terms of the conceptual approach taken and the values chosen by March to test differences between exploitation and exploration in his original model. Three different ratios of expert knowledge collected were also evaluated (*rEX* = 1%; 10%; 100%). As before, the accuracy of average individual knowledge (*Y*) represented the dependent variable.

GROUPS		COUNT	SUM	AVERAGE	VARIANCE	CONSTANT
'top-down1", occasiona	al use (pKM=0.1), $d = 4$	40	18.33	0.45825	0.011488	environmenta
'top-down2", occasiona	al use (pKM=0.1), $d = 4$	40	25.066	0.62665	0.005541	turbulence,
'top-down1", frequent u	use (pKM= 0.5), d = 4	40	19.535	0.488375	0.009492	p4 = 0.02
'top-down2", frequent u	use (pKM= 0.5), d = 4	40	27.77	0.69425	0.004907	Percent exper
'top-down1", over-depe	endent use (pKM=0.), $d = 4$	40	17.6	0.44	0.007194	-stored -consensus,
'top-down2", over-depe	endent use (pKM=0.), $d = 4$	40	27.432	0.6858	0.005467	rEX=1%
bottom-up1", occasion	al use (pKM=0.1), d = 4	40	20.469	0.511725	0.006008	
bottom-up2", occasion	al use (pKM=0.1), d = 4	40	30.568	0.7642	0.005841	
bottom-up1", frequent	use (pKM= 0.5), d = 4	40	19.998	0.49995	0.006156	
bottom-up2", frequent	use (pKM= 0.5), d = 4	40	30.102	0.75255	0.006323	
bottom-up1", over-dep	bendent use (pKM=0.), $d = 4$	40	17.466	0.43665	0.007998	7
bottom-up2", over-dep	bendent use (pKM=0.), $d = 4$	40	27.501	0.687525	0.007964	
VARIATION	SS	df	MS	F	P-VALUE	F-CRIT
Between Groups	15.634725	15	1.042315	140.22347	2.4501E-188	1.682432
Within Groups	4.638343	624	0.007433			
Fotal	20.273068	639				
"top-down1" = high	exploitation (p1=0.5), lo	w explora	tion, (p2=0.1), no turnover (p3=0.00), tiers	=4
"top-down2" = high	exploitation (p1=0.5), lo	w explora	tion, (p2=0.1), turnover (p3=	=0.02), tiers=4	
"bottom-up1" = low	exploitation (p1=0.1), h	igh explora	ation, (p2=0.	5), no turnover	(p3=0.00), tier	s=4
	v exploitation (p1=0.1), h					

Figure 4 broadly visualizes our findings for our third experiment, with the vertical bars representing standard errors. Of note, in the far, left-hand corner we indicate the same organization with no knowledge management system. Overall, our results reveal that whether a knowledge management system positively influenced the accuracy of average individual knowledge depended on the values of p1, p2, and pKM. On average, at the 0.0005 significance level, increasing the collective probability of norms of use and influence knowledge management system (pKM) increased the accuracy of average individual knowledge, but only to a certain point. Beyond pKM = 0.5, increasing the collective probability of norms of use and influence of a knowledge management decreased accuracy of average individual knowledge regardless of the presence or absence of personnel turnover. See Table 2 and Figure 4 for details.

Additionally, keeping all other variables constant, increasing the ratio of expert knowledge collected (rEX) reduced the accuracy of average individual knowledge in an organization. We observed that attempting to discern true knowledge through an increasing number of individuals in an organization resulted in the accuracy of average individual knowledge (Y) approximating 0.500 correlation with external reality (i.e., only half of the knowledge beliefs held are correct).



Experiment 4: supporting computational variations

To alleviate concerns that the findings of this study could be a result limited to its definition of low, moderate, and high levels of different constructs, a fourth experiment was performed in which 6,000 random samples are drawn from the total population of all possible organizational strategies. Exploitation (p1) and exploration (p2) were assigned random values ranging from 0.1 to 0.9 according to a flat distribution. Personnel turnover (p3) and environmental turbulence (p4) were assigned random values ranging 0.000 to 0.040 (to three decimal places) with a flat distribution. We intentionally varied the number of tiers (d) for different hierarchical organizations from 2 to 5. The accuracy of average individual knowledge (Y) was the dependent variable.

We performed a weighted-least-squares regression with the number of tiers (d) as the weight to adjust for heteroscedasticity by allowing the variance of the residuals to be approximately equal. This study expected such heteroscedasticity: as the number of tiers increase in an organization, so does the number of managers with direct reports. Additional managers result in additional fragmentation of knowledge within an organization, leading to increased variation of knowledge throughout the organization. The fourth experiment observed no auto-correlation to the residuals. Moreover, a plot of the number of tiers against the standardized residuals confirmed that the variance in the error term increased as the number of tiers increased (see Figure 7 in the Appendix for details).

The first regression did not consider the effect of a knowledge management system, only the effect of the number of tiers in an organizational hierarchy. An interaction term was included between exploitation (p1) and the number of tiers in the hierarchical organization (d), based on the results of the second experiment. The resulting first regression produced an adjusted-R² of 0.376 with all coefficients possessing p-values < 0.05, including the interaction term. The model itself was significant at the 0.0005 level with an F-value of 604.722 (see Figure 5 for details). A check of the variance inflation factors for the regression demonstrated some correlation between (p1) and the interaction term (p1 and d), which is expected but not alarming.

The main effects of exploitation (p1) and exploration (p2) were both positive, with exploitation somewhat greater in magnitude. The main effect of turnover (p3) was positive, while the main effect of turbulence (p4) was negative. For

every one-hundredth of a unit increase in turnover (p3), the accuracy of average individual knowledge increased by 0.02118 on average (one-hundredth, or 1/100 of a unit increase is reported because p3 is a probability between 0 and 1). Similarly, for every one-hundredth of a unit increase in turbulence (p4), the accuracy of average individual knowledge decreased by 0.05646. These two findings are consistent with March's original observations and supports hypotheses H2a and H2b.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin- Watson			
1	.614ª	.377	.376	.197121	1.970			
in b. D	teractP1Depth ependent Vari	able: corrOrgC	CMatch	°3, probP1, probP ghted by countDe				
			ANOV	Ą b,c				
Model		Sum of Squares	df	Mean Square	F	Sig.		
1	Regression Residual Total	140.984 232.867 373.852	5993		604.722	.000ª		
in b. D	redictors: (Cor teractP1Depth ependent Vari:	able: corrOrgC	Match	23, probP1, probP ghted by countDe				
in b. D	redictors: (Cor teractP1Depth ependent Vari:	able: corrOrgC Squares Reg	CMatch ression - We	ghted by countDe Coefficien	oth S ^{a,b}	-	T	
in b. D	redictors: (Cor teractP1Depth ependent Vari:	able: corrOrgC Squares Reg Ur	Match	ghted by countDe Coefficien	oth s ^{a,b}		Collinearity	<u></u>
in b. D c. W Model	redictors: (Cor teractP1Depth ependent Vari eighted Least	able: corrOrgC Squares Reg	CMatch ression - We nstandardized Coefficients Std. E	ghted by countDe Coefficient Standardti Coefficien rror Beta	s ^{a,b} red t	Sig	Collinearity Tolerance	Statistics VIF
in b. D c. W	redictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant)	able: corrOrgC Squares Reg	CMatch ression - We nstandardized Coefficients Std. E 658	ghted by countDe Coefficient Standardti Coefficien rror Beta 006	s ^{s,b} red t 117.57	2 .000	Tolerance	VIF
in b. D c. W Model	redictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant) probP1	able: corrOrgC Squares Reg Ur B	CMatch ression - We nstandardized Coefficients Std. E 658 170	ghted by countDe Coefficient Standardti Coefficien rror Beta 006 014	s ^{a,b} red its 117.57 300 12.33	2 .000 0 .000	Tolerance .176	VIF 5.688
in b. D c. W Model	redictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant) probP1 probP2	able: corrOrgC Squares Reg Ur B	CMatch ression - We nstandardized Coefficients Std. E 658 170 124	ghted by countDe Coefficient Standardti Coefficien rror Beta 006 014	s ^{a,b} red its 117.57 300 12.33 215 21.03	2 .000 0 .000 3 .000	Tolerance .176 1.000	VIF 5.688 1.000
in b. D c. W Model	redictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant) probP1 probP2 probP3	able: corrOrgC Squares Reg Ur B 2.	CMatch ression - We standardized Coefficients Std. E 658 170 124 118	ghted by countDe Coefficient Standardi Coefficien rror Beta 006 014 006	s ^{a,b} red ts 117.57 300 12.33 215 21.03 182 17.87	2 .000 D .000 3 .000 5 .000	Tolerance .176 1.000 1.000	VIF 5.688 1.000 1.000
in b. D c. W Model	edictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant) probP1 probP2 probP3 probP4	able: corrOrgC Squares Reg Ur B B 2. -5.	CMatch ression - We standardized Coefficients Std. E 658 170 124 118 646	ghted by countDe Coefficient Standardi Coefficien 006 014 006 118	s ^{a,b} red ts 117.57 300 12.33 215 21.03 182 17.87 488 -47.87	2 .000 0 .000 9 .000 5 .000 6 .000	Tolerance .176 1.000 1.000 .999	VIF 5.688 1.000 1.000 1.001
in b. D c. W Model	redictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant) probP1 probP2 probP3	able: corrOrgC Squares Reg Ur B B 2. -5. epth -	CMatch ression - We coefficients Std. E 658 170 124 118 646 055	ghted by countDe Coefficient Standardi Coefficien 006 014 006 118 118	s ^{a,b} red ts 117.57 300 12.33 215 21.03 182 17.87 488 -47.87 446 -17.10	2 .000 0 .000 9 .000 5 .000 6 .000 4 .000	Tolerance .176 1.000 1.000	VIF 5.688 1.000 1.000 1.001 6.549
in b. D c. W	edictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant) probP1 probP2 probP3 probP4 interactP1D- countBreadt	able: corrOrgC Squares Reg Ur B B 2. -5. h	CMatch ression - We coefficients Std. E 658 170 124 118 646 055 001	ghted by countDe Coefficient Standardi Coefficien 006 014 006 118 118	s ^{a,b} red ts 117.57 300 12.33 215 21.03 182 17.87 488 -47.87 446 -17.10	2 .000 0 .000 9 .000 5 .000 6 .000 4 .000	Tolerance .176 1.000 1.000 .999 .153	VIF 5.688 1.000 1.000 1.001
in b. D c. W Model 1 a. D	edictors: (Cor teractP1Depth ependent Vari- eighted Least (Constant) probP1 probP2 probP3 probP4 interactP1D countBreadt ependent Vari-	able: corrOrgC Squares Reg Ur B B 2.	CMatch ression - We Coefficients Std. E 658 170 124 118 646 055 001 CMatch	ghted by countDe Coefficient Standardi Coefficien 006 014 006 118 118	s ^{a,b} red 117.57 300 12.33 215 21.03 182 17.87 488 -47.87 446 -17.10 297 -21.02	2 .000 0 .000 9 .000 5 .000 6 .000 4 .000	Tolerance .176 1.000 1.000 .999 .153	VIF 5.688 1.000 1.000 1.001 6.549

More importantly, the interaction term (between p1 and d) was negative, with a magnitude roughly one-third the value of the main effect of exploitation. The effect of exploitation on the accuracy of average individual knowledge depends on the number of tiers in an organization. This finding is consistent with the second experiment and hypothesis H1, where increasing exploitation had negative consequences for a multi-tier organization, but not for a flat organization (i.e., d = 2). At d = 4, for a one-hundredth of a unit increase in exploitation (p1), the accuracy of average individual knowledge decreased by 0.00050. At d = 5, for a one-hundredth of a unit increase in exploitation (p1), the accuracy of average individual knowledge decreased by 0.00105. See Figure 5 for details.

Next, we performed a second regression to consider the additional effect of increasing or decreasing the collective probability of norms of use and influence of a knowledge management system (pKM) and the effect of collecting knowledge from wider or narrower ratios of expert individuals (rEX). We did not include a squared-term to examine the curvelinear effect of pKM, in part because that trend was clearly observed in our ANOVA and in part because

the trend was only seen when turnover was present (i.e., we would expect an interaction effect as well). We limited our investigation to the main effect of pKM and rEX only.

Model	R	R Square	Adjust R Squ		d. Error of Estimate	Durbin- Watson				
1	.406ª	.165		163	.207456	2.000				
cou b. Dej	untBreadth, pi pendent Varia	robKM, interai able: corrOrg(ctP1Dep CMatch	ith	bbP4, probP3, d by countDep					
			P	NOVA ^{b,c}						
Model		Sum of Squares	0	df M	ean Square	F	Sig	a.		
1	Regression Residual Total	50.794 257.840 308.633		8 5991 5999	6.349 .043	147.527	- 13	.000ª		
cou b. Dej	dictors: (Con IntBreadth, pi pendent Varia	robKM, interac able: corrOrg(ctP1Dep CMatch	oth	bbP4, probP3, d by countDep					
cou b. Dej	dictors: (Con IntBreadth, pi pendent Varia	robKM, interad able: corrOrgC Squares Reg	ctP1Dep CMatch	th - Weighte		th a,b				
cou b. Dej C. Wei	dictors: (Con IntBreadth, pi pendent Varia	robKM, intera able: corrOrgC Squares Reg Ur	ctP1Dep CMatch ression nstanda <u>Coefficie</u>	th - Weighte rdized ents	d by countDep Coefficients Standardiz Coefficient	th ;a,b s		201-	Collinearity	Trakelaka
cou b. Dej c. Wei Model	dictors: (Con IntBreadth, p pendent Varia ighted Least	robKM, intera able: corrOrgC Squares Reg	ctP1Dep CMatch Iression nstanda Coefficie	th - Weighte rdized ents Std. Error	d by countDep Coefficients Standardize	th sa,b sa t	40	Sig.	Collinearity Tolerance	Statistics VIF
cou b. Dej C. Wei	dictors: (Con IntBreadth, pi pendent Varia	robKM, intera able: corrOrgC Squares Reg	ctP1Dep CMatch ression nstanda <u>Coefficie</u>	th - Weighte rdized ents	d by countDep Coefficients Standardiz Coefficient Beta	th ;a,b s		Sig. .000	and a state of the	VIF
cou b. Dej c. Wei Model	dictors: (Con intBreadth, pi pendent Varia ighted Least	robKM, intera able: corrOrgC Squares Reg Ur B	ctP1Dep CMatch Iression Standar Coefficie	th - Weighte rdized ents Std. Error .007	d by countDep Coefficients Standardizi Coefficient Beta	th ed s 94.3 94.3	10	.000	Tolerance	VIF 5.65
cou b. Dej c. Wei Model	dictors: (Con intBreadth, p pendent Varia ighted Least (Constant) probP1	robKM, intera able: corrOrgC Squares Reg Ur B	nstanda Coefficie 8656 050	th - Weighte rdized ents Std. Error .007 .014	d by countDep Coefficients Standardizi Coefficient Beta	th ad s t 99 3.5	10 85	.000 .000	Tolerance .177	VIF 5.65 1.00
cou b. Dej c. Wei Model	dictors: (Con intBreadth, p pendent Varia ighted Least (Constant) probP1 probP2	robKM, intera able: corrOrgC Squares Reg	nstanda Coefficie 1.656 .050 .031	rdized ents Std. Error .007 .014 .006	d by countDep Coefficients Standardizi Coefficien Beta .0 .0	th sa,b sd s yd 99 3.5 61 5.1	10 85 96	.000 .000 .000	Tolerance .177 .999	VIF 5.65 1.00 1.00
cou b. Dej c. Wei Model	dictors: (Con intBreadth, p pendent Varia ighted Least (Constant) probP1 probP2 probP3	robKM, intera able: corrOrgC Squares Reg Ur B B -2	ctP1Dep CMatch Iression Standar Coefficie 856 050 031 .260	rdized ants <u>3td. Error</u> .014 .006 .124	d by countDep Coefficients Standardiz Coefficien Beta .0 .0 .0 .0	th ed s 99 3.5 61 5.1 25 2.0	10 85 96 04	.000 .000 .000 .036	Tolerance .177 .999 .999	VIF 5.65 1.00 1.00 1.00
cou b. Dej c. Wei Model	dictors: (Con intBreadth, p pendent Varia ighted Least (Constant) probP1 probP2 probP3 probP4	robKM, intera able: corrOrgC Squares Reg Ur B B B -2 -2	ctP1Dep CMatch Iression S656 050 031 260 .675	rdized ants <u>3td. Error</u> .014 .006 .124 .124	d by countDep Coefficients Standardiz Coefficien Beta .0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0	th 22 23 24 24 24.3 99 3.5 61 5.1 25 2.0 54 -21.5	10 85 96 04 83	.000 .000 .000 .036 .000	Tolerance .177 .999 .999 .998	VIF 5.65 1.00 1.00 1.00 6.49
cou b. Dej c. Wei Model	dictors: (Con intBreadth, pi pendent Varia ighted Least (Constant) probP1 probP2 probP3 probP3 probP4 interactP1Da countBreadt probKM	robKM, intera able: corrOrgC Squares Reg Ur B B B -2 h -2 -2	ctP1Dep CMatch rression 656 .050 .031 .260 .675 .007 .000 .068	th - Weighte - Weighte - Meighte - M	d by countDep Coefficients Standardiz Coefficient Beta 0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0	th (a,b 2:d 3:3 9:9 3:5 6:1 5:1 2:5 2:0 5:4 -2:1.5 6:6 -2:1 5:2 -3:1 3:3 -11.2	10 85 96 04 83 65 30	.000 .000 .036 .000 .029 .002 .002	Tolerance .177 .999 .999 .998 .154 .519 .998	VIF 5.65 1.00 1.00 1.00 6.49 1.92 1.00
cou b. Dej c. Wei Model	dictors: (Con intBreadth, pi pendent Varia ighted Least (Constant) probP1 probP2 probP3 probP3 probP4 interactP1De countBreadt	robKM, intera able: corrOrgC Squares Reg Ur B B B -2 h -2 -2	ctP1Dep CMatch Iression Coefficie 656 .050 .031 .260 .675 .007 .000	rdized ants <u>3td. Error</u> .014 .006 .124 .124 .003 .000	d by countDep Coefficients Standardiz Coefficient Beta 0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0 .0	th 223 234 243 294.3 99 3.5 61 5.1 25 2.0 54 -21.5 66 -2.1 52 -3.1	10 85 96 04 83 65 30	.000 .000 .000 .036 .000 .029 .002	Tolerance .177 .999 .999 .998 .154 .519	VIF 5.65 1.00 1.00 1.00 6.49 1.92

As before, we performed a weighted-least-squares regression. This regression considered the effects of a knowledge management system. Again, an interaction term was included between exploitation (p1) and the number of tiers in the hierarchical organization (d), based on the results of the second experiment. The resulting regression produced an adjusted-R² of 0.165 with all coefficients significant at p < 0.05. The model itself was significant at the 0.0005 level with an F-value of 147.527 (see Figure 6 for details). The variance inflation factors are below the critical value for concern.

Importantly, pKM and rEX were both negative as predicted by H3 and H4. For every one-hundredth of a unit increase in pKM, the accuracy of average individual knowledge decreased by 0.00068 on average (one-hundredth, or 1/100 of a unit increase is reported because p3 is a probability between 0 and 1). Similarly, for every one-hundredth of a unit increase in rEX, the accuracy of average individual knowledge decreased by 0.00111. Though smaller than the coefficients reported in the first regression model without a knowledge management system, p1 and the interaction term (p1 and d) are similar in sign and approximate scale compared to one another, consistent with the second experiment and the first regression. Equally, the coefficients for p3 and p4 are now smaller; supporting

the idea that a knowledge management system both lessens the negative effects of environmental turbulence, but also supplants the positive effects of turnover in an organization by retaining knowledge (right or wrong) after individuals depart the organization. With a knowledge management system in place, for every one-hundredth of a unit increase in turnover (p3), the accuracy of average individual knowledge increased by 0.00260. For every one-hundredth of a unit increase in turbulence (p4), the accuracy of average individual knowledge decreased by 0.02675. See Figure 6 for details. Additionally, for a screenshot example of the model running a simulation, see Figure 8 located in the Appendix.

Conclusions

This study extends March's classic model to account for hierarchical organizations. In the absence of personnel turnover, a knowledge management strategy of high exploitation and low exploration reduces the accuracy of average individual knowledge levels for a multi-tier hierarchical organization. Keeping all other variables constant, increasing the number of tiers in a hierarchical organization increased this reduction in accuracy, but this reduction can be addressed by altering strategic behaviors.

We note that this study potentially is limited in its approach by considering simulated data; however, our methodology is in alignment with March's original model and perhaps the only way to consider the consequences of different exploitation and exploration strategies for more than 6,000 different organizations.

From this study, it appears that hierarchical organizations that rely on a heavy top-down exploitative knowledge management strategy, combined with little or no personnel turnover, may not be appropriate for adequately adjusting to turbulent environments. Traditionally, such organizations have been explicitly defended as being best suited for maintaining their own internal reality or organizational code (e.g., most military or government institutions) or implicitly defended based on accumulated or negotiated norms of behavior (Cyert and March 1963). This study demonstrates that when confronted with a rapidly changing external reality, heavy top-down knowledge management exploitative hierarchical organizations may not be sufficiently agile to maintain their accuracy with a changing, external reality.

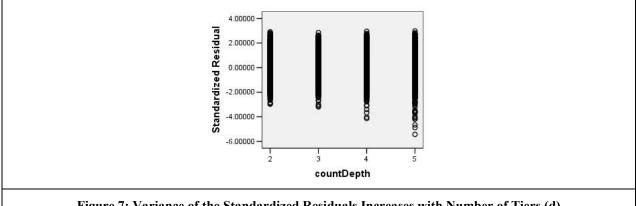
Moreover, increasing the likelihood of individuals learning from a knowledge management system has significant positive effects for a multi-tier, hierarchical organization – with the magnitude of these positive effects dependent on strategic choices of structure and knowledge management system use. Similarly, increasing the ratio of expert knowledge collected reduces the accuracy of average individual knowledge in an organization. Thus, another implication from our study is that knowledge management efforts need to collect and share expert knowledge only from the top performing individuals, and organizations should employ a knowledge management system for selective cases versus moderate or frequent use. Our data also shows that if overused, a knowledge system can inhibit exploratory organizational learning.

Hence, one method to counteract the negative consequences of a top-down knowledge management strategy in such a multi-tier, hierarchical organization is to encourage personnel turnover coupled with use of a knowledge management system providing the expert insights of the top (1% in this simulation) individuals. We note that changing structure to a "flatter form" may represent a significant difficulty for large organizations (i.e., the ubiquity of hierarchies in such instances); that said, our findings demonstrate that the impact of structure can be mitigated by strategic choices of influence (p1 and p2) and strategic choices of knowledge management system use (embodied by pKM and rEX on our model). Additionally, we note one final observation: by extending March's model of exploration and exploitation, our data demonstrates that a bottom-up strategy demonstrates greater resilience to environmental turbulence. We believe this work helps add to the accumulation of wisdom addressing the complexities of organizational learning and its "myopias" (Simon 1991; Levinthal and March 1993).

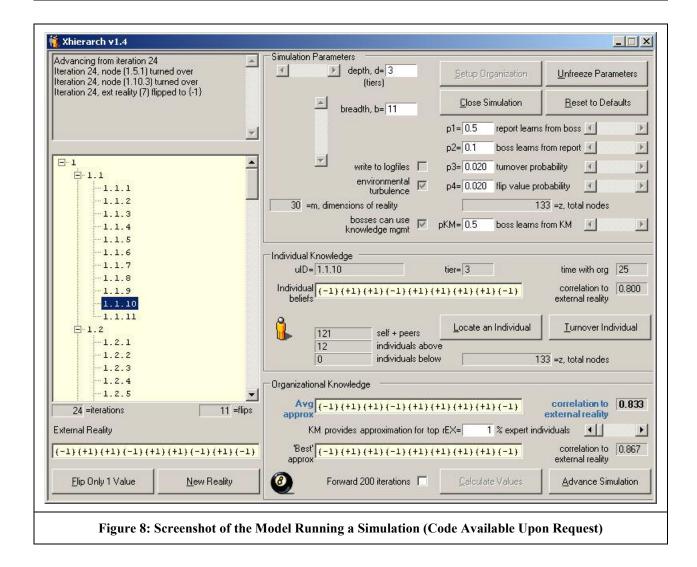
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Appendix







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