A Dynamic Model on Organizational Learning and Forgetting based on "Serious" Errors

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Abstract

Organizational science research has established that organizations experience an oscillation cycle of learning and forgetting, particularly in response to "serious" errors. Yet, the intricacies of this dynamic process and its implications on organizational behavior remain underexplored. This study introduces a dynamic model theorizing how organizations transition from a non-safety focus to a safety-focus following "serious" errors, a phenomenon we term as the learning phase, which subsequently diminishes over time, a phenomenon we term as the forgetting phase. Our investigation reveals three critical insights: First, the time delay in an organization's response to "serious" errors significantly influences the pattern and efficacy of learning in subsequent oscillation cycles. Second, the prevailing organizational culture, especially in terms of resource focus between innovation and safety in the existing period, profoundly affects future probability of errors. Third, the established safety threshold within an organization exerts a lasting impact on safety outcomes in the long run. This paper contributes to the understanding of organizational learning and forgetting dynamics by elucidating the effects of "serious" errors, thereby offering a comprehensive framework for enhancing organizational resilience and performance.

Keywords: Organizational learning, Organizational forgetting, serious errors, system dynamics

1. Introduction

On January 28, 1986, the space shuttle *Challenger* exploded soon after takeoff. Seventeen years later, the space shuttle *Columbia* met a similar fate, where it disintegrated during reentry after a successful mission on February 1, 2003, despite a seemingly successful mission (Vaughn, 2005). Official reports have shown that not only are both accidents systemic organizational failures but were also preventable (Feynman, 1986; Gehman et al., 2003). Subsequent analysis indicated that management and organizational factors played a significant part in both accidents; with managerial and engineering decisions creating systemic risk that persisted over the years (Vaughn, 2005).

In the wake of these tragedies, organization science researchers have delved deeper to investigate the mechanisms by which organizations learn from, and sometimes forget, serious errors. These errors are defined as "organizational processes that result in failure with significantly adverse outcomes" (Haunschild et al., 2015). Studies across various safety-critical industries – ranging from airline (Haunschild & Sullivan, 2002a), mining (Madsen, 2009), or orbital launch (Madsen & Desai, 2010) - have revealed a clear pattern: the more severe the failure, the greater the impetus of organizational learning. Furthermore, the temporal proximity of such failure events affects the value of the experience associated with such events, with recent experiences deemed to be more valuable than older ones (Argote et al., 1990; Arthur & Huntley, 2005; Epple et al., 1991; Ingram & Baum, 1997). Madsen & Desai (2010) notably found that knowledge acquired from failure experience decayed more slowly than knowledge acquired from success experience.

Despite these insights, the question remains what is the impact of an organization's response to a major disaster on its future performance. This gap in understanding persists, however, not due to a lack of theory or data. For example, Madsen (2009) offers a theory on how prior organizational experience with disaster affects the likelihood that organizations will experience future disasters. Desai (2015) discusses how the heterogeneity of error types affects organizational learning and Park et al. (2023) differentiate the learning outcomes based on the root causes of failures. Furthermore, the majority of organizational learning studies have been empirical by nature, relying on extensive real-world data to validate hypothesis concerning how organizations learn from failures (Haunschild et al., 2015; Park et al., 2023). This suggest that the field may benefit from a methodological advancement that can capture the dynamic and often complex nature of organizational learning in the aftermath of "serious" errors.

Organizations are complex adaptive systems, with which members interact, make decisions and collectively learn and evolve over time. This systemic complexity prompts a need to view errors as dynamic rather than static occurrences. Lei & Naveh (2023) highlight this difference in the perspective gap in their systematic review of organizational studies. They propose a paradigm shift from viewing errors as isolated incidents to understanding them as processes—sequences of emergent, interconnected events that adapts throughout the firm's structure and operations. This "error-as-process" perspective recognizes errors as cascade (or chain) of emergent triggers that a firm develops, changes, and adapts through the system over time. Furthermore, Lei et al. (2016) articulate the need for a methodological realignment in research to test theoretical models with temporal nature of errors, stating: "Researchers should build a better alignment between theory and method to understand the processes and changes related to errors over time and thus to assess causality. The temporal-focused research approach can enable error scholars to test key predictions about how key dynamics of error situations evolve over time and begin specifying the causal links and feedback" (p. 1340).

Despite the future research recommendation, human ability to infer the behavior of low-order dynamic systems is known to be limited (Diehl & Sterman, 1995; Sterman, 1989). This limitation has led to two main camps of research interests and distinct schools of thought. First, the more traditional research approach predominantly focuses on monocausal models, which are a commonly seen in organization science research. Such models formulate hypotheses that explore the relationships between specific behavioral and environmental variables. For instance, concerns about how reactions from security analysts, an external factor, shape organizational learning after "serious" errors (Polidoro & Yang, 2017), and concerns regarding how the depreciation of organizational knowledge affects quality performance in car manufacturer vendors (Agrawal & Muthulingam, 2015).

While these models offer clarity in understanding the relationships between independent and dependent variables, they often do not capture the full complexity of the organization's dynamics. On the other hand, those that dispense with mono-causality often embrace this complexity by leaning towards dynamic models. These models move beyond mono-causality to embrace the complex interaction among variables and how they interact over time. Such dynamic approaches offer a systematic perspective that generate insights often missed in monocausal models that account for feedback loops, time delays, and nonlinearities inherent in organizational systems. This systemic view is not only more reflective of the multifaceted nature of organizations but also allows for a deeper exploration of the emergent properties and patterns that arise from the interactions within these systems.

In this study, we take a different approach to the existing literature. We propose to use simulation models to demonstrate how time delays and a firm's attitude towards safety incidents can lead to significant different long-term performance outcomes. It is important to clarify that our model introduces neither new data nor variables and does not test the strength of relationships between variables. Instead, our contribution lies in the derivation of new insights from well-established variables in the existing literature.

To develop our simulation model, we follow three steps. First, diverging from the norm of conventional System Dynamics models that rely on behavior-over-time graphs from empirical data, we adopt a grounded theory approach to inductively build theory from existing theoretical frameworks (Strauss & Corbin, 1994). Next, we formulate our conceptual model based on the narrative theories in the literature. Lastly, we translate the conceptual model into a structural stock and flow diagram support with mathematical functions to produce and generate dynamic behaviors.

Our findings not only align with previous work but also provide a layer of specificity to the discourse. Our contribution is fourfold: 1) Our model advances the literature on organizational learning and forgetting, particularly in response to "serious" errors. This progression is achieved through an extensive review of the existing literature, allowing for a more nuanced understanding of these processes. 2) The dynamic nature takes a first step to provide "error-as-process" perspective on the research question that is complex and adaptive. 3) We present the practicality and relevance of using the system dynamics model to investigate complex organizational phenomena. The model focus on how organizations response to "serious" errors over time and highlights potential policy interventions that could fortify organizational resilience and performance, such as balancing innovation with safety and establishing effective safety thresholds. 4) Lastly, this research extends its impact beyond organizational science, contributing to related fields such as safety science, operations management, and risk management.

The insights derived from our model are threefold. First, we provide a feedback perspective on how organizations adjust their attention prior to and after the occurrence of errors. Second, our findings reveal that firms undergo the process of organizational learning and forgetting when they encounter "serious" errors. Third, we observe that organizations with a strong emphasis on safety, which address potential errors more diligently, tend to experience fewer errors. Consequently, these organizations accumulate less knowledge derived from failures. Additionally, we note that the environments with higher volatility of errors tend to provoke more risk-taking behaviors in a profit-focused firm. Our study underscores the importance of a dynamic approach to simultaneously consider both learning and forgetting within organizations. This approach is crucial to understand how varying degrees of safety culture and adaptability in learning contribute to organizational performance over time.

As the renowned statistician George Box aptly stated, "All models are wrong, but some are useful." This principle holds true for our structural model, which, despite its utility, is not without limitations. Certain assumptions inherent in the model might pose challenges to the validity of our analysis, as indicated by the relevant literature (Forrester, 1994). However, it is essential to recognize that any analytical journey must begin with a foundational step. The model we have developed adds complexity by considering important interactions and feedback loops to the existing thread of literature, yet it also crystallizes insights into the dynamic nature of organizational learning and forgetting in the context of "serious" failures. It is crucial to focus on the core dynamics presented by this model and leverage it as a foundation for future explorations. By doing so, we can build upon the insights gleaned and continue to refine our understanding of these critical organizational processes.

The remainder of the paper is organized as follows. In § 2, we present a detailed walkthrough of the steps to develop the conceptual model that derived from building theory from theory. In §3, we develop and analyze a formal model of organizational learning and forgetting due to "serious" errors. In §4, we present the model simulation results, including the firm's response to severe errors, the adaptive dynamics of organizational knowledge and attention in response to a single exogenous shock, and comparative dynamics on safety and non-safety-focused firms under environmental volatility. In § 5, the conclusion and implications for future research are discussed.

2. The Method

We explore the mechanisms that produce variations of organization's performance through time due to "serious" errors by developing a formal model. Rather than building our theory from raw empirical data that are well documented and articulated in the system dynamics community (Repenning & Sterman, 2002; Rudolph & Repenning, 2002), we build our conceptual model from a grounded theory approach, building theory from theory (Strauss & Corbin, 1994). We reviewed the literature in organizational learning (Argote, 2011; V. M. Desai et al., 2020), organizational forgetting (Mariano et al., 2020a, 2020b), and error management in organizations (Lei & Naveh, 2023). Recent trends in organizational studies, especially in error research, use empirical data to induce hypothesized theories (Baum & Dahlin, 2007; Haunschild & Sullivan, 2002b; Madsen, 2009). Hence, although our study does not build on empirical data, the conceptual model that we developed in this study is a synthesis of the findings of these papers that are based on empirical data.

With the motivating example of *Challenger* and *Columbia* space shuttle accidents, we pursued the following steps to carry out our theory development. First, we follow the steps of ground theory building to build theory from theory (Strauss & Corbin, 1994, Suddaby, 2006), starting by translating constructs and relationships in the space shuttle accident and pharmaceutical industry "serious" errors narrative (Haunschild et al., 2015) into a system dynamics language of causal loop diagrams (Forrester, 1997; Sterman, 2010). We also incorporate some fragments of other research findings, proposing constructs and relationships that augment feedback structures that were not explicitly explored in the current literature (Davis et al., 2007). For instance, we incorporate the attention-based view of the organization, linking the accumulation of organizational knowledge to complete the feedback loop (Park et al., 2023). This feedback structure is further inspired by Lei et al.'s (2016) review of how errors interact and reach dynamic equilibrium in organizations, emphasizing the need for firms to constantly align themselves to cope with persistent disruptions and conflicting forces. Our model reflects this necessity to correct and learn from errors over time, thereby enabling resilience and sustainability. Illustrative examples of such dynamics are drawn from studies by Ramanujam & Goodman (2011) and Rudolph & Repenning (2002), which provide empirical contexts to our theoretical constructs.

Second, we translate the causal loop diagram to a stock-flow diagram. It was at this point that we realized that it is crucial to identify the stocks in our system dynamics model that clearly depicts organizational behavior. This is a critical process to transform mostly error-as-event, a static view of errors, into an error-as-process, a dynamic view of errors in the model. Third, for our stock and flow diagram, we incorporate equations so that it is a formal model that produces simulation runs. For example, "organizational knowledge" is presented as a stock in the model, and the rate of inflow and outflow is experience and depreciation, respectively.

The benefit of constructing a formal model by theorizing about the dynamic processes allowed us to identify inconsistencies with existing theories and synthesize fragments of theories and logical gaps (Sastry, 1997; Sterman, 1994). We followed standard system dynamic modeling formulation to account for the model's robustness (Sterman, 2010, p. 86).

3. The Model

3.1. How Organizational Knowledge Accumulates and Erodes

We begin with the specification of conceptual model with the notion of organizational learning. Scholars predominantly define organizational learning as a change in the organization's knowledge that occurs as a function of experience (e.g., Fiol & Lyles, 1985). It is commonly agreed that experiences are accumulated into organizational knowledge, thereby influencing and refining future behaviors, actions, and beliefs (Argote & Miron-Spektor, 2011; Cyert & March, 1963; Levitt & March, 1988). This knowledge is understood as the collective capability of organizational members, developed through work and shaped by historical collective understandings and experiences (Chiva, 2005; Tsoukas & Vladimirou, 2001).

While researchers have identified various types of experiences that impact a firm organization learning behavior, such as direct versus indirect experience (Haas & Hansen, 2005), the novelty of the experience (Katila & Ahuja, 2002), and the ambiguity of the experience (March, 2010); our study focuses on experience from failure. In this context, researchers indicate that such failure events incentivize members to accumulate the necessary knowledge to anticipate and prevent future incidents (Baum & Dahlin, 2007; V. M. Desai, 2011; Madsen, 2009). Hence, in our conceptual model, we hypothesize that failure experience is accumulated into organizational knowledge, which is observed in form of performance improvements and the likelihood of future success.

On the other hand, alongside the accumulation of knowledge through failure experience, there is also potential for erosion, a process termed knowledge depreciation (Argote et al., 1990) and knowledge loss (Daghfous et al., 2013) in the literature. This concept falls under organizational forgetting, which (de Holan & Phillips, 2004) describe as "the loss, voluntary or otherwise, of organizational knowledge" (p. 1606). It has been observed that organizational knowledge is often unsystematic and opportunistic, leading to situations where previously acquired knowledge is overlooked (Geroski & Mazzucato, 2002).

Thus, in our model, we conceptualized organizational knowledge, denoted as K, as a stock or level variable. Acknowledging that knowledge cannot be acquired by managers instantaneously but gradually, we proposed that it's rate of change is governed by two factors: experience and depreciation.

$$\mathrm{K} = \int_{t_0}^{t} \left(\frac{Max(0, \mathrm{S_t} - K_t)}{T_e} - \frac{Max(0, K_t - S_t)}{T_d} \right) dt \ + k_{t_0} \quad (1)$$

The first component, experience, is defined as the rate at which knowledge accumulates within an organization, it is calculated as experience learned per month. This rate of inflow is calculated as the difference between the current state of the knowledge, K_t, and the firm's attention to safety, denoted as $\mathrm{S_t}$ (detailed explanation of $\mathrm{S_t}$ is documented in Section 3.2.), and divided by the time it takes for an experience to grow within the organization, T_e. The second component of the integral function represents the rate of knowledge depreciation. The stock of knowledge, K, is reduced by this outflow. Similarly, depreciation rate is determined by the gap between the knowledge, K_t, and attention to safety, $\mathrm{S_t}$, over the time it takes for knowledge to depreciate within the organization T_d. In summary, when a firm's focus on safety, denoted as, S_t, surpasses its current level of knowledge, represented by K_t, it indicates that managers have recognized the need for acquiring more knowledge. This situation leads to a positive inflow of experience into the organization's knowledge stock. On the other hand, when the firm's attention to safety, S_t is less than the organization's knowledge K_t, there is an outflow of knowledge depreciation in the firm. We also assume that organization firm is equipped with an initial knowledge, denoted as k_{t_0}, and a baseline. Next, we specify the organization's probability of error, P_{error}, as a sigmoid function of organization's knowledge, K, the safety threshold, χ, pressure from manager, p, and magnitude of the chance of errors, γ (scaling factor).

$$P_{error} = \gamma * (1 - \frac{1}{1+e^{-p(K-\chi)}}) \quad (2)$$

We then model the error occurrence, E, as a stochastic function comparing between organization's chance of error P_{error} and a random uniform distribution function representing the randomness of the environment. Let T be the current time and be T_{int} the integer part of T. Chance of Errors, P_{error}, is a probability value between 0 and 1. The random variable U follows a uniform distribution in the interval [0, 1] with a specified seed for reproducibility. The conditional expression of Error Occurrence, E, can then be defined as:

$$E = \begin{Bmatrix} 1 & if\ T = T_{int}\ and\ U < P_{error} \\ 0 & otherwise \end{Bmatrix} \quad (3)$$

3.2. Attention based View of the Organization

In the second half of the conceptual model, we take an attention based view of the firm (Ocasio, 1997; Ocasio et al., 2020) and the notion of limited organizational attention (Simon, 2013), to hypothesize how firms respond to serious errors. The concept of attention has been coined prominently in organization learning theories, where firm behavior is the result of how firms' channel and distribute their attention to organization members. Ocasio (1997) defines attention as "the noticing, encoding, interpreting and focusing of time and effort by organizational decision makers" (p. 189).

Similar to our transformation from qualitative framework to quantitative model for organizational knowledge, we conceptualized "Attentional Resource", denoted as A, as a stock or level variable that accumulates over time. Recognizing that this resource cannot be changed directly by managers, but it rather grows or depletes gradually, we propose two primary mechanisms of change: attention growth and attention erosion. Attention resource, represented mathematically below, captures these dynamics:

$$A = \int_{t_0}^{t} \left(\frac{Max(0, E*(A^* - A_t))}{T_g/16} - \frac{A_t}{T_e} \right) dt + r_{t_0} \quad (4)$$

Attention growth, the first component in the integral function, is predicated on the idea that, organizations adjust their attention in response to the occurrence of "serious" errors, E, as the firm tries to minimize the gap between the Desired Attention goal A^* and the current attention level, A. Last, the growth rate is moderated by, T_g, representing the time the it takes for attention to grow post-error[1]. The second component addresses attention erosion. Given the assumption that attentional capacity among organization members are inherently limited, not all organizational experience are converted into knowledge (Gavetti et al., 2012). The erosion rate is modelled as the current the level of attention resource divided by the average time of attention erosion, T_e. We also incorporate an initial of attention resource level, r_{t_0}, representing the firm's attentional resource baseline.

Last, we propose firm's attention on safety follows a sigmoid function to normalize it to the range of 0 and 1, as formulated in Equation (5). This equation incorporates the Attention resource, A, the normal attention resource on safety (attention capacity), N, and firm's attention capability, α. The normal attention resource on safety signifies the baseline level of attention that a firm should allocate to safety-related concerns. Deviation from N the normal attention resource may indicate a shift in focus. Firm's attention capability, α, is the firm's ability to consciously regulate its attention allocation. It influences how quickly or gradually the firm adjusts its attention to safety concerns in response to changes in its attention resource (A) relative to the normal attention resource (N). A higher α value implies a more rapid adaptation of attention, while a lower value suggests a slower response.

$$S = \frac{1}{1+e^{-\alpha(A-N)}} \quad (5)$$

This formulation adheres to the attention-based view, which posits that if the experience gained exceeds the normal attention resource, then firm will wittingly or unwittingly choose to allocate their finite attention to a particular experience and knowledge while ignoring others (Ocasio, 1997; Simon, 2013).

3.3. Model Overview

[1] We divided T_g with 16 due to model boundary issue

This section presents an overview of the model that consists of two negative feedback loop, as illustrated in Figure 1. The two feedback loops, "Organizational Learning" and "Organizational Forgetting" due to "serious" errors describes the dynamic organizational behavior. Initially, an occurrence of a "serious" error, triggers an increase in the rate of attention growth, resulting in an accumulation of the attentional resource stock. This surge of attentional resources, enhance the organization's focus on safety, thereby facilitating an inflow of experience into the organization's knowledge. In organization behavior studies, this stage exemplifies organizational learning triggered by "serious" errors.

Subsequently, as organizational knowledge increases, implying superior safety performance, the probability of error occurrence diminishes. This reduction in the probability of errors leads to a stagnation in attention growth within the organization, accumulating into a gradual depletion of attentional resources. As attentional resources diminish, a lower incoming experience rate contributes to the depletion of organizational knowledge, which increases the occurrence of errors. This phase represents the phenomenon of organizational forgetting, also known as knowledge depreciation. This concept refers to the concept of knowledge decaying unintentionally and gradually through time, as evidence in Argote et al., (1990) Benkard (2000) &Thompson (2007). It is important to note that the term "organizational knowledge" in this model specifically pertains to safety-related knowledge, given our focus on the dynamics of learning and forgetting in the aftermath of "serious" errors. During this phase, knowledge – particularly that which pertains to "serious" errors – diminishes, and increases the likelihood of error occurrence. Moreover, in line with the principles of the attention-based perspective on organizations, firm's attention is a limited resource. Such limited resource is typically turned into competition in organization as tensions between conflicting goals, such as safety and profit goals (e.g., Gaba & Greve, 2019; Madsen, 2013). Haunschild et al. (2015) found that the focus of organizational attention oscillates between safety (i.e., errors) and innovation (i.e., patents) goals based on the recency of errors, concluding that failure incidents plays a dual role that "pushes organizations toward a focus on safety while pulling them away from competing foci such as efficiency or innovation" (p. 1683). That is, the allocation of attention in organizations due to failure may trigger learning, but simultaneously, other organizational goals may suffer as a result.

Ultimately, this initiates a recurring cycle. Figure 2 depicts the dynamic behavior generated by the proposed simulation model. Firm oscillates between safety focus (avoid doing things that might result in a "serious" error such as developing a new drug that is not safe) and non-safety focus (avoid not doing things that is appropriate, such as not producing a drug that is safe) in the wake of accidents or "serious" errors.

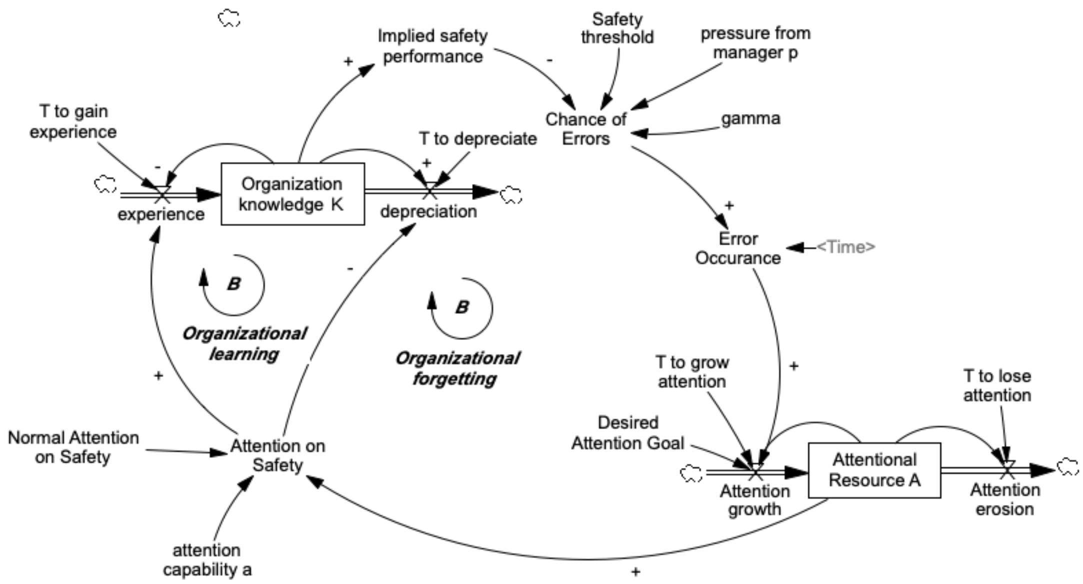

Figure 1. Model Structure Overview[2]

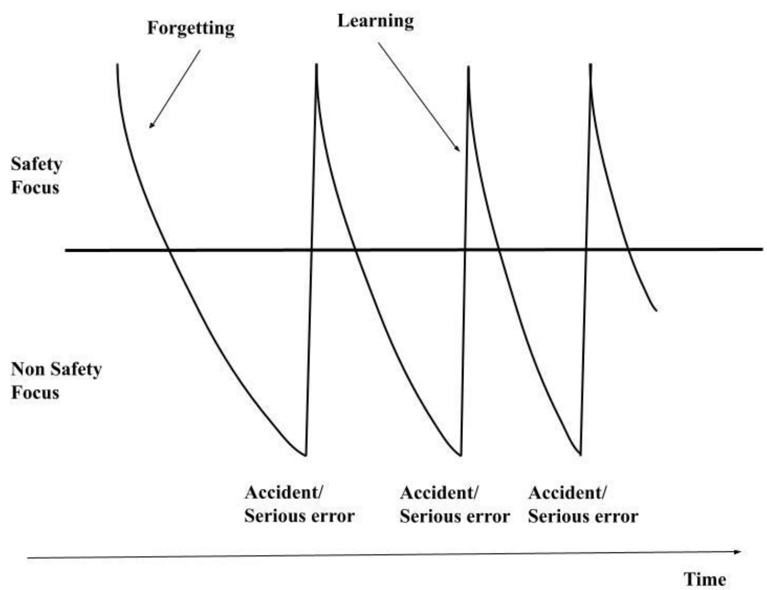

Figure 2. Organizational Oscillation between Safety and Non-Safety Foci due to "Serious" Error (Adapted from Haunschild et al. (2015))

4. Model Analysis

4.1. Firm's Response to "Serious" Errors

[2] Note: Arrows indicate the direction of causality. Plus, or minus signs on the linkage indicate the polarity of the relationships: a plus signs denotes that an increase in the independent variable causes the dependent variable to decrease, a decrease causes a decrease. Similar, a minus sign indicates that an increase in the independent variable causes the dependent variable to decrease. The rectangle box sign represents the stock variable, that accumulates and dissipates, where the flow variable, next to the stock variable, are presents in the diagram as "pipes" with "valves".

We begin the analysis by reproducing the dynamics outlined in the narrative theory of organization learning and forgetting due to "serious" errors, spanning a duration of 100 months. Figure 4 shows a set of model runs, illustrating how a firm responds to "serious" errors occurring at month 20. We show three possible scenarios, each corresponding to a different severity level of the impact of errors (moderate, significant, and critical). We quantify the severity level impact errors as one, five and ten, respectively to differentiate their impact (Figure 3). This scale does not correspond to any real-world metrics but serves as a conceptual tool to demonstrate the varying intensities of "serious" errors in our simulation runs. Figure 4-a shows the firm's attention resource response to these varying levels of impact errors. In each case, immediately after the occurrence of "serious" errors at month 20, there is a marked spike in the firm's attention resource. Later, however, the intensity of the attention resource subsequently erodes over time, leading to a decline attention resources. In short, the intensity of the incident drives varying levels of attention, thereby creating a distinct behavioral pattern of organizational knowledge over time.

This observed pattern aligns with the attention based view of the theoretical framework of crises as proposed by Kudesia & Lang (2023). Given that organizational members are inherently limited in their attention capacities (Ocasio, 1997), failures within organizations act as strong signals, motivating organizational members to allocate significant amount of resources towards preventing similar future failures (Dahlin et al., 2018; V. M. Desai et al., 2020; Madsen & Desai, 2010). There are two factors that distinguish the three behavioral patterns. First, the level of severity failures prompts organizations to allocate different levels of attention. For instance, accidents of larger magnitude, which are measured in terms of accident cost and level of injuries motivates organization members to pay more attention and invest more in activities that can reduce the risk of future accidents (Madsen, 2009). Consequently, in our example, the attention resource allocation during the critical impact error scenario is the highest among the three. Second, the recency of the incident affects attention. Over time, the impact of the event on attention resources diminishes as many problems are resolved or better managed (Haunschild et al., 2015). Hence, a consistent pattern of decreasing attention over time is observed in all three of our scenario examples.

Simultaneously, Figure 4-b illustrates the firm's trajectories of organization knowledge under the same three scenarios. Unlike attention, organization knowledge requires time to develop. This process begins once an incident is internalized and transformed into "experience", and subsequently being learned and integrated as organizational knowledge (Argote & Miron-Spektor, 2011). In each scenario, there is an initially gradual increase in knowledge following the impact of a "serious" error. Nevertheless, this knowledge gradually depletes through time as organizations forgets voluntarily or not (de Holan & Phillips, 2004). As expected, the critical impact error scenario accumulates a larger amount of organization knowledge compared to the others as it develops the most attention resource. Furthermore, the sample runs reveal a delay mechanism in the accumulation of organizational knowledge. As Rahmandad (2008) suggests, such delays add complexity to the learning process and result in performance heterogeneity in organizations.

It is important to emphasize that in our model, "organizational knowledge" specifically refers to knowledge pertaining to safety, instead of knowledge on other organizational profit goals such as efficiency and innovation. This focus is essential for understanding the relationships between failures and knowledge. In the example simulation runs, the upward trajectory in Figure 3-b represents the phenomenon of "organization learning", while the downward trend signifies the "organizational forgetting" phenomenon, a concept explored in detail by Haunschild et al. (2015).

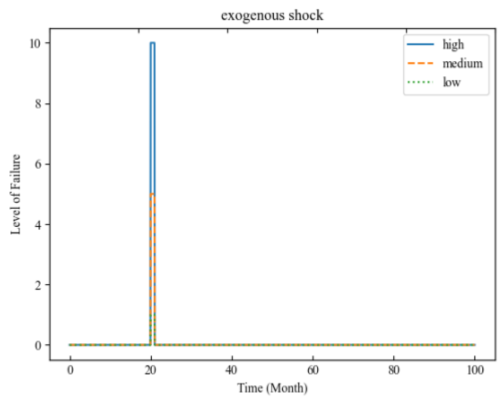

Figure 3. Three Different Levels of level of "Serious" Errors as Shocks

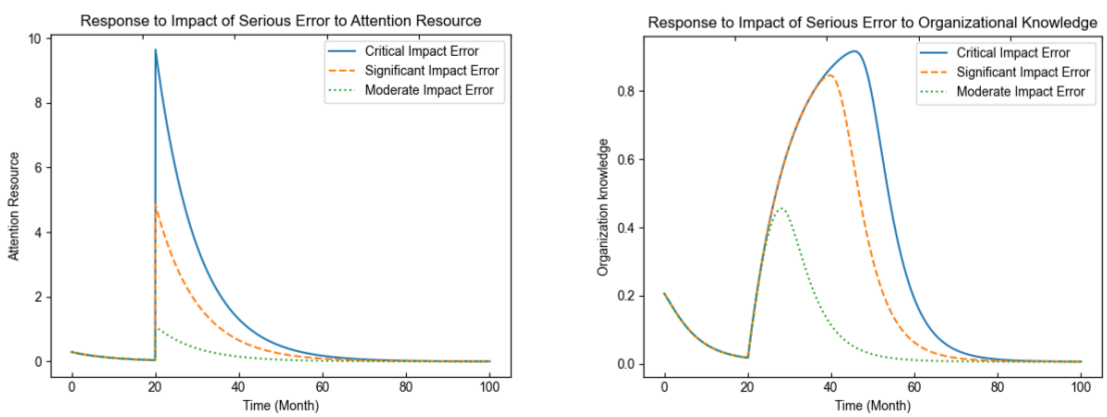

Figure 4. Firm Response to a "Serious" Error and its Impact on Organizations Attention Resource and Knowledge

4.2. Adaptive Dynamics of Organizational Knowledge and Attention in Response to an Exogenous Shock

To analyze the dynamic behavior of organizational knowledge and attention resources in response to "serious" errors, we begin with two simple cases in which a firm encountered "serious" errors under two types of assumptions: deterministic and stochastic.

In the deterministic case, a firm encounters a "serious" level 3 error at month 20 (as illustrated in the previous example in Section 4.1). In this case, attention spikes at this point (Figure 5a), and organizational knowledge begins to accumulate slowly post-incident, reflecting the firm's effort to fix and address the failure. The gradual accumulation of organizational knowledge, even after the peak of the attention resource, suggests an ongoing learning process within the firm, such as improving its safety protocol and gaining insights to prevent future incidents. Following the "serious" errors, both attention resources and organizational knowledge revert to zero. Since the firm does not experience any "serious" errors anymore, no attention is needed, and organizational knowledge is depleted gradually. We then introduce a phase portrait, representing the trajectories of the firm through the phase space.

Figure 5b represents the state of the attention resource against the state of organizational knowledge. Each directional line shows the trajectory, and each error shows the direction of the flow from that point. The trajectory in the phase portrait shows how the state of the system evolves after the shock. The directional lines on the upper right indicate that after the spike of attention, the system starts to move back towards the origin, where both “attention resource” and “organizational knowledge” are at lower levels. In this case, the path that leads back to the origin (lower left in the plot) suggests that the firm’s process and responses to shocks are resilient, bringing the system back to equilibrium. This resiliency is due to the balancing feedback loop, where the firm’s mechanisms for dealing with errors counteract the disturbance caused by the shock.

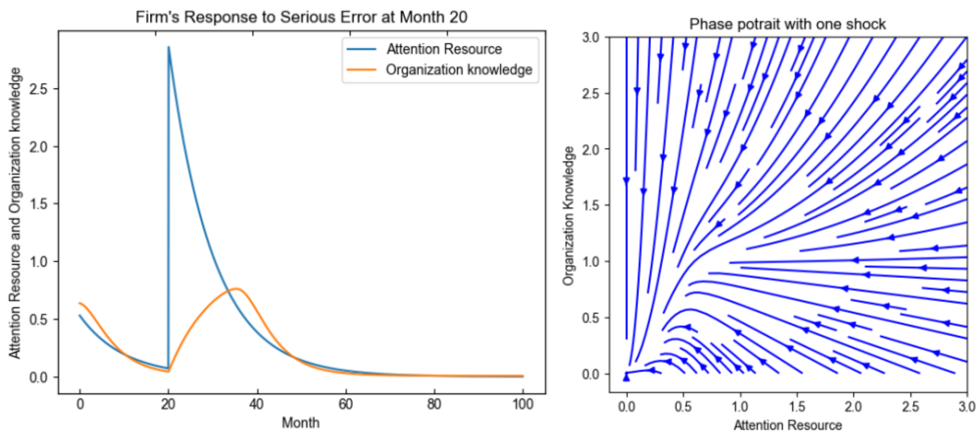

Figure 5. (a) Firm’s Response to a Single Shock and (b) Phase Portrait Diagram.

In the second case example, rather than treating “serious” errors as an external shock, we assume firm’s responses to errors are directly affected by their safety performance, represented by organizational knowledge in this study, which directly impacts their likelihood of errors. Here, firm’s attention growth is contingent upon the probability of error occurrence at time t. The revision is motivated by the idea that a firm’s attention growth is not only influenced by exogenous factors, but it is tied to its own safety performance and the probability of errors occurring. We revised the attention growth equation as follows:

$$\text{Attention growth rate} = \frac{Max(0,\ P_{error} * (A^{*} - a))}{T_g/16}$$

The model starts with a randomly generated state of error probability of 3.5% at Month 0 (Figure 6a). As the probability of errors diminishes, there’s a corresponding decrease in the accumulation of attention resources, leading to minimal accumulation of knowledge. However, the little organizational knowledge implies poor safety performance, thereby heightening the likelihood of errors, a pattern of oscillation thus emerges (Figure 6b). This oscillation gradually dampens as the firm settles into a new equilibrium state, each characterized by reduced error probability and shorter spikes in attention, leading to a diminishing oscillatory behavior in organizational safety knowledge.

Eventually, both attention resource and organization knowledge reached a state of equilibrium. As attention resource returns to its initial baseline, it suggests that the firm does not allocate as much attention to the error. Meanwhile, organizational knowledge remains at a slightly elevated level compared to the initial state, indicating that there is some retention of the insights gained from the crisis.

Figure 7 depicts the phase portrait of the firm's dynamic behavior, mapping attention resource in response to changes in organizational knowledge. The plot shows one or more points where the trajectory converges, indicating a stable equilibrium point where the system eventually settles. As the amplitude of the oscillatory behavior diminishes the phase diagram spirals inwards. There are two main trajectories observed: First, in the lower left of the graph, where the firm is low on attention and knowledge, an increase in attention (moving right along the x-axis) leads to a rise in organizational knowledge (move up along the y-axis), indicating the "learning" phase after the incident. In this phase, the balancing feedback loop –"organizational learning" dominates the behavior of the system.

Second, in the upper right on the graph, where resource attention and organizational knowledge are high, a decrease in attention results in a gradual reduction of organizational knowledge (moving diagonally towards to lower left of the graph). This trajectory represents the "forgetting" phase, characterized by the balancing loop of "organizational forgetting." It is clear that the firm tries to find the stable equilibrium post-error occurrence, aiming to return to baseline levels. However, in the real-world scenarios, the oscillation never dies away, due to the continuous disruption with noise such as "serious" errors. In the next section, we present scenarios considering noise in the system.

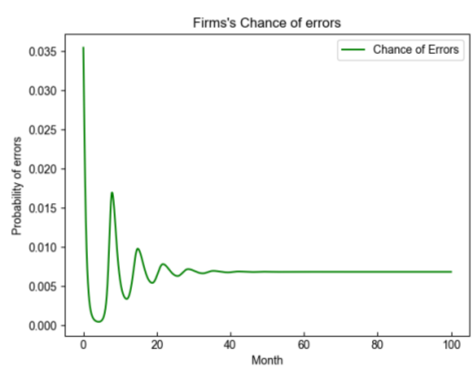

Figure 6. Firm's Probability of Errors

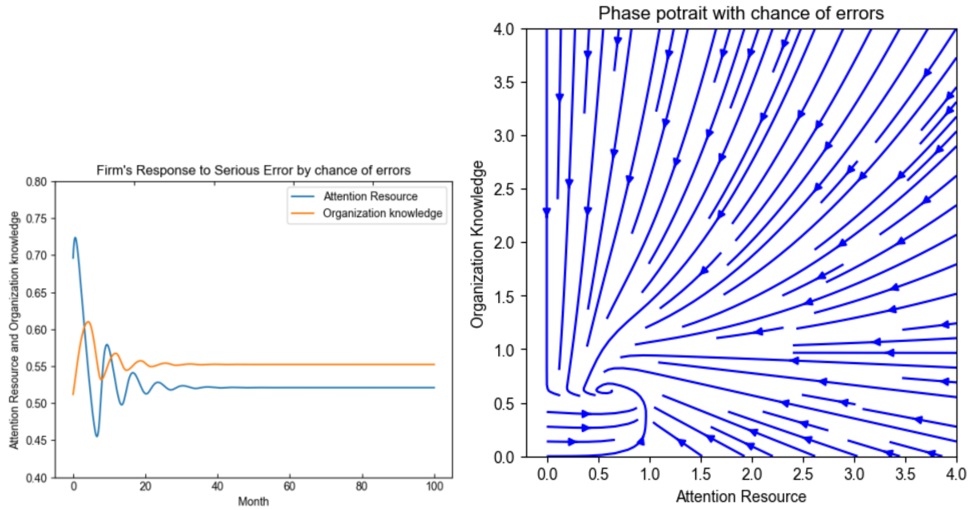

Figure 7. Firm's Response in Probability of Errors – Stochastic Case

4.3. Comparative Dynamics on Safety and Non-Safety Focused Firms under Environmental Volatility

In this section, we explore how variability in environmental volatility influence the firm's organizational knowledge. To incorporate the effect of environmental uncertainty, we represent noise by modeling probability of error with the – exogenous shock to attention growth – as pink noise process, ϵ , where normally distributed white noise is exponentially smoothed to create first-order autocorrelation with time constant of δ and standard deviation σ.[3]

$$E = \left\{ \begin{matrix} 1 & if\ T = T_{int}\ and\ \ \epsilon < P_{error} \\ 0 & otherwise \end{matrix} \right\}$$

To present the main finding, we consider two firms responding to two types of environmental variability. The first firm prioritizes safety, and responds aggressively to failures, particularly during moments of high error probability ($\chi = 0.2$). On the other hand, the second firm focuses on non-safety goals, usually profit related such as efficiency and innovation ($\chi = 0.8$) and adopts a more measured response to potential failures.

All parameters remain constant across simulations except for the standard deviation of the error noise, which is increased fourfold (std = 0.5) in the second simulation, though the mean failure rate remains unchanged (shown in Figure 8). The noise parameter ranges from -0.5 to 0.5 with a mean of 0.15, implying that lower values denote a riskier environment. This approach allows us to systematically assess the influence of heightened environmental volatility on the strategic decision-making of firms with different core foci.

[3] See (Sterman, 2010) for an comprehensive examination of using pink noise as a testing input in continuous time simulation models.

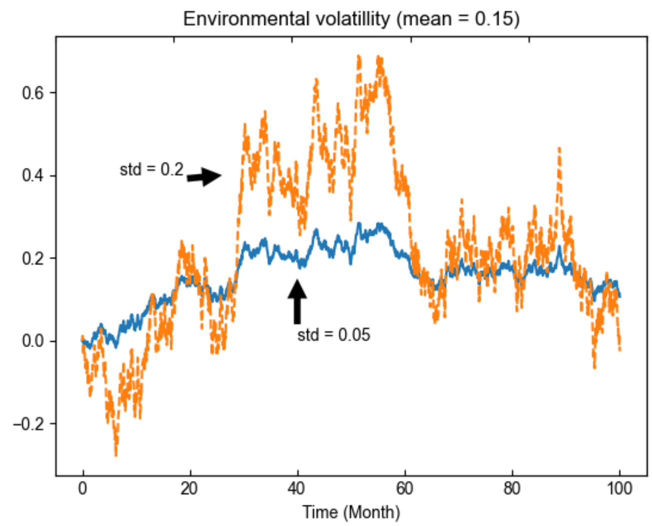

Figure 8. Environmental Volatility

We test how the firms react within an environment characterized by low volatility, meaning that the environment is generally stable with minimal unexpected disruptions or potential failure events (as indicated by a standard deviation of 0.05 in Figure 8). Under these conditions, the profit-focused firm sustains a higher level of organizational knowledge (Figure 9). This is attributed to its exposure to a greater probability of errors, necessitating increased attention to address the environmental noise. As the probability of errors is determined by the organizational knowledge and the safety threshold, the safety-focused firm, adhering to a more conservative policy regarding potential errors, experiences fewer instances of error occurrences, thus reducing the likelihood of "serious" errors.

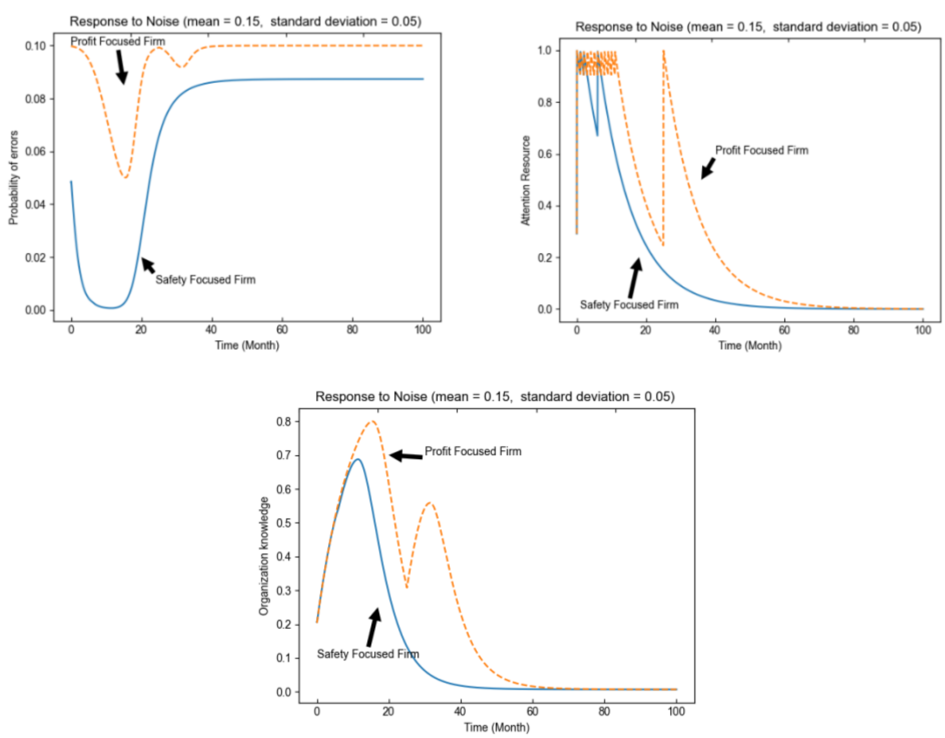

Figure 9. Safety and Profit Focused Outcomes, One Environmental Volatility with $\sigma = 0.05, \delta = 10\ months$

In the second simulation run, we increased the standard deviation of the environment noise to 0.5, keeping the remaining parameters values identical. The environmental shock of safety condition is depicted by the orange line in Figure 8, where there is a very unsafe period between month 0 and 20 and a very safe period between the month of 30 and 60. Utilizing the same seed variable for both simulations ensures that the general shape of the environmental conditions remains consistent, though the severity varies. This results in an extremely unstable environment with significant fluctuations.

The profit-focused firm displays a higher probability of errors compared to the safety-focused firm, primarily due to its less rigorous approach to potential error conditions (Figure 10). This necessitates the allocation of additional effort and attentional resources to mitigate the errors, which consequently leads to an accumulation of organizational knowledge over time. Under such a volatile environment, the disparity in how each firm addresses potential errors becomes apparent, with the profit-focused firm ultimately enhancing its organizational knowledge as a byproduct of its response strategy.

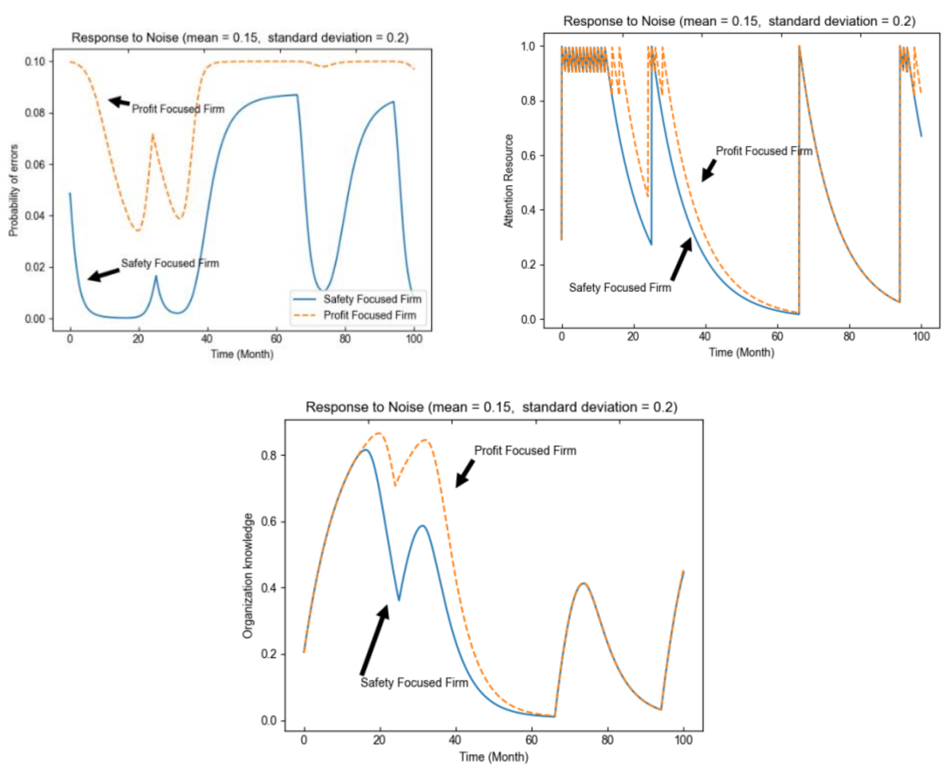

Figure 10. Safety and Profit Focused Outcomes, One Enviromental Volatility with $\sigma = 0.2, \delta = 10\ months$

5. Discussion and Implications for Future Research

Our analysis offers two contributions in understanding the impact of "serious" errors on organizational learning and forgetting. First, we treat errors as a trigger for the dynamic interplay between learning and forgetting within the organization over time, emphasizing the temporal aspects of errors and the response to errors. While an existing research has examined how “serious” errors can trigger learning and forgetting (Haunschild et al., 2015), we focus on the feedback loops and delays in these systems. We delved into how “serious” errors, which later are translated into experiential learning, affect long term accumulation of organizational knowledge. Second, we showed that the relationship between “serious” errors and organization’s learning and forgetting is far more complex that monocausal models might suggest. Our systemic perspective, grounded in the attention-based view of organizations, examines the effect of firms’ limited attention to safety issues over time in response to “serious” errors, and how this influences organizational knowledge acquisition. Specifically, we investigate the safety culture within organizations, exemplified by managerial attitudes towards errors, represented by safety thresholds in our study, plays a significant role in shaping the long-term behavior of organization knowledge.

It is important to acknowledge that the model from these insights derived is far simpler than any real-world system. As organizations are complex adaptive systems, varying in size, culture, structure and goals, the time to learn and forget is different among firms. For instance, (Huberman, 2001) explores the variation in learning rates observed across firms. Thus, treating errors as a homogenous event with predictable outcomes across all organizations is an oversimplification. Our model, however, represents an initial step towards understanding these core dynamics under theoretical assumptions. The nature and impact of “serious” errors can vary significantly across different contexts. For example, the contrasting consequences of a pharmaceutical company releasing a harmful drug versus a railway traffic control center experiencing a train accident.

There are, however, limitations to our proposed model. First, our model is a theoretical model, though derived from a theory, is not yet validated with empirical, real-world data. Second, we have not captured the novelty of the errors. We have assumed uniformity in error characteristics, but in reality, the novelty of the error could significantly influence the learning and/or the forgetting rate of the organization, as well as the transformation and internalization of the experience. For example, a firm may pay more attention to a new type of “serious” errors than errors that have occurred in the past.

Despite these limitations, our model offers two crucial insights: First, a more comprehensive understanding of how organizations learn and forget in response to “serious” errors requires the consideration not only the severity of the error, but also the novelty of the error. Secondly, it is still premature to assume that all errors induce similar dynamics in organizational learning and forgetting processes. In summary, our research contributes to a deeper understanding of the nuanced and complex relationship between serious errors and organizational learning and forgetting, highlighting the need for further empirical investigation in this area.

6. Conclusion

Overall, in addition to these contributions, we hope that our model provides a systemic perspective to the understanding of the oscillatory behaviors in organization learning and forgetting prior and post-error. Our approach builds upon the error-as-process perspective, incorporating an analysis of the feedback mechanisms and time delays that influence an organization's accumulation of knowledge over time. While we focus primarily on the shifting attention in response to “serious” errors, this research has the potential to be extended to other precursors, such as sudden changes in staff retention or other significant organizational shifts.

A key avenue for future research lies in the empirical testing of our model using real-world data. Given that concepts such as experience, knowledge, and attention are inherently challenging to quantify, we advocate for the incorporation of established survey methodologies that can translate these abstract constructs into measurable, quantitative data. We suggest that future studies could gather survey data on organizational knowledge and attention, collecting information from managers and staff within organizations over time. This approach will provide a more robust foundation for validating the proposed theoretical model.

Finally, while it is an unrealistic goal to eliminate all “serious” errors, and the oscillation cycle they generate, understanding the underlying mechanisms of such phenomena is crucial. This can potentially help organizations to better anticipate and mitigate the impacts of errors, thereby enhancing the learning and forgetting process.

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