A Generalized System Dynamics Model for Managing Transition-Phases in Healthcare Environments

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Abstract

Process change is often difficult to manage, let alone to predict. In this paper, adaptation function theory is used to illustrate how a system dynamics-based model can be used to anticipate the effects that process change policies and strategies will have on change execution. The adaptation function is a form of learning curve that incorporates a performance goal following an exponential growth/decay behavior. Adaptation function focuses on learning by doing, thus making it ideal to assess a transition-phase between two processes; that is, the process to implement a new process. The methodology proposed delineates how system archetypes can be used as the building blocks to model learning by doing transition-phases. In addition, the methodology is validated through the establishment of the theoretical foundations to build a transition phase management model, contextualized in an electronic health records (EHR) system implementation process. The resulting model and framework is validated through extremes testing and potential applications for the methodology and EHR model are discussed.

Keywords: Transition-phase management, system dynamics modeling, systemic archetypes electronic health records, process change.

1. Introduction

The healthcare industry in the USA has been challenged by the need to migrate their information systems to a unified Electronic Health Records (EHR) system. Challenges have arisen from incompatibility with their current methods and the vendor's systems to inadequate transition planning. The focus of the work presented in this paper is on how to manage the transition phase to an EHR system; that is, how to determine the resource and time requirements based on a desired implementation outcome. The authors propose a systemic (holistic) approach to assist healthcare managers in planning and executing their transitions towards an EHR system. The goal of the proposed research is to develop a model to assist healthcare managers to optimize the quality of implementation, resource allocation and completion time. The model uses parameters obtained from mental databases and quantitative historical data, following system dynamics modeling practices[1].

The proposed approach, called transition-phase management, builds upon Calvo-Amodio etc al[2] theoretical framework by combining concepts from organizational learning theory, system dynamics, systems science, and project management. To combine the concepts, total systems intervention[3] and the creative methodology design[4] meta-methodologies are used.

Several attempts to combine managerial philosophies such as total quality management, six sigma, theory of constraints, reengineering, and discrete event simulation[5] to overcome their inherent limitations have been explored. Yasin[6] conducted an investigation to evaluate the effectiveness of several managerial philosophies applied to a healthcare environment. The authors report that "it is equally clear from the data that some tools and techniques were more difficult to implement than others", implying that many of the failures were due to inadequate implementations or lack of understanding of the scope. From a systems thinking perspective, these two types of failures in implementing a methodology are explained by the methodology's inability to deal with specific problem contexts. This supports the point that a complement artist systems thinking approach can be explored by taking an atypical approach that tackles ""small"" problems, instead of large and complex ones.

1.1. *What is a System?*

As shown in Fig. 1, a system is a perceived whole whose elements are interconnected and have a purpose in a given context. It is framed or perceived and defined by the analyst (e.g. observer, person who will act upon it, stakeholder, etc.) based on his/her set of *a priori* beliefs and feelings (Weltanschauung or world view).The analyst will assign a purpose and boundaries to the system. There is a dynamic interaction between the system's boundaries and purpose within the context, which defines what the system is to the analyst. The interaction is dynamic, because as the analyst's knowledge about the system and its context grows, his/her perception on what the purpose is and where the boundaries are will change. The analyst weltanschauung is fluid, and it changes as more knowledge about the system, its context, purpose and boundaries become available.

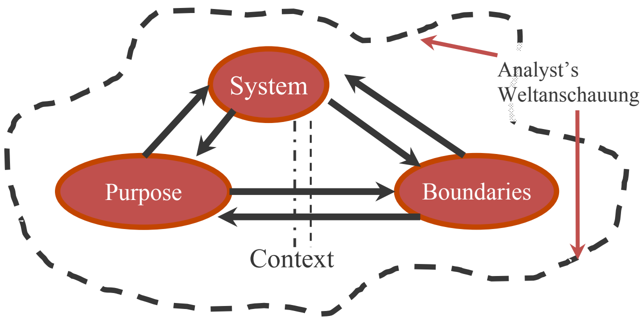


Fig. 1. Definition of a System

1.2. *Efficiency, Efficacy, and Effectiveness*

When creating any model, the purpose, objectives, and benefits expected, ends, resources available and means must be clearly stated. Proper allocation of means (such as technology and staff) and ends (reduction of clerical errors or better flow of patient care) can be balanced through their efficient, efficacious, and effective use within a model. In this context, we define efficiency as the ratio between resources used and their product (or what the outcome is); that is, doing things at the right cost. A system is efficient if the value of the outcome or the benefit is perceived to be higher than the value of the resources employed to produce/generate it.

Efficacy refers to the ability that a system has to perform as and/or do what it is designed to do. The ends are what matter, regardless of the means employed; that is, doing things the right way. It is then, that achieving efficacy and efficiency may result in a paradox, as optimizing both may be not possible.

Effectiveness refers to the alignment of what the system actually does and what the system is supposed to do. Effectiveness questions the adequacy of the outcome produced by the system; that is, doing the right things. For instance, a system may be efficient and efficacious within its own design but still fail to perform as desired because it is not aligned with its context or purpose, thus failing to be effective[a].Hence, a model is only effective if its performance, regardless of its complexity, is aligned with what it is expected to do.

2. Overview of System Dynamics Theory

System dynamics (SD) creates diagrammatic and mathematical models of feedback processes of a system of interest. Models represent levels of resources that vary according to rates at which resources are converted between these variables. Delays in conversion and resulting side-effects are included in models so that they capture in full the complexity of dynamic behavior. Model simulation then facilitates learning about dynamic behavior and predicts results of various tactics and strategies when applied to the system of interest[7].

SD was developed by Jay W. Forrester to model feedback loops in systems where non-linear time dependent interactions are present.SD presents a powerful approach to modeling complex systems in accordance to what their internal structure and interactions actually are, and not in accordance to what statistics and/or mathematical models suggest alone. Feedback is present in non-linear systems where its components sustain complex interactions and that emergent properties arise from such interactions. With the use of level and rate variables, it is possible to model the interactions and feedback loops between system components. Dynamic modeling can help identify lack of understanding of a process or system, and to identify what are the most important variables in a process or system[8].

Peter Senge[9] advocated for the use of systems thinking as the quintessential tool to enhance the efficacy of managerial endeavors. As Forrester's disciple, Senge's approach is focused on the use of system dynamics, and causal loop models.

The foundation blocks, or the common structures that describe all systems, are the level and rate equations[10, 11].Level equations result from integrations of flows proceeding from rate inflow equations minus the integration of rate outflows equations over time. In its simplest form, a rate equation depends on the state of the level variable. A rate equation regulates, depending on the state of the level variable the flow rate as shown by Esq. (1) and (2).

$$Level_t = \int_{t=0}^{n} Inflow\ Rate - \int_{t=0}^{n} Outflow\ Rate \quad (1)$$

$$Rate_t = \frac{dLevel}{dt} = Inflow\ Rate_t - Outflow\ Rate_t \quad (2)$$

There are two graphical tools to represent the relationships expressed in Eqs. (1) and (2): Causal Loop Diagrams, and Level and Rate diagrams (a.ka. Forrester Diagrams).A causal loop diagram is a graphical representation of the interactions between the level and rate variables in the system. In Fig. 2 we can see the graphical representation of Esq. (1) and (2).The state of the level is determined by the inflow and outflow rates. The arrows connecting the variables indicate the nature of the relationship (feedback) between them. A positive feedback means that the rate change will be in the same direction as the change observed in the level.

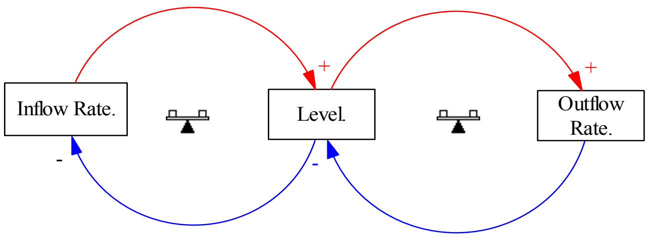


Fig. 2. Causal Loop Diagram

A negative feedback means that the rate change will be in the opposite direction of the change observed in the level. For instance, if the state of the level increases, the inflow rate will decrease.

Fig. 3 shows a Level and Rate diagram where the rate of flow and stock of goods, materials, money, information, etc. is represented by valves and stock

[a]It is important to note that defining efficiency and efficacy carefully is important to approach the expected behavior of the model.

components. The valves (Inflow and Outflow Rates) are controlled by the feedback received from the stock variable (Level).

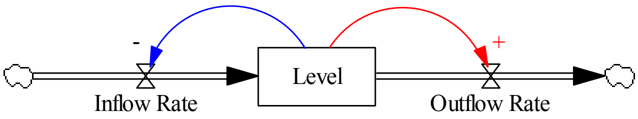


Fig. 3. Rate and Level Diagram

A system dynamics model is constructed, according to Forrester,[1011] information from mental, written, and numerical databases (Fig. 4). Different components of the model are extracted from these databases allowing the model to replicate the real system characteristics accurately.

Barlas[12] presents a guideline on generalized steps employed to develop a system dynamics model:

(i) Problem identification
(ii) Model conceptualization (construction of a conceptual model)
(iii) Model formulation (construction of a formal model)
(iv) Model analysis and validation
(v) Policy analysis and design
(vi) Implementation

The construction of a conceptual model is generally aided by the use of causal loop diagrams. Systems think authors such as Peter Checkland[11], [13], [13]–[30] advocate for the use of mental models to better understand, or learn about the system at hand.

''The real value of modeling is not to anticipate and react to problems in the environment, but to eliminate the problems by changing the underlying structure of the system''.[1]Causal loop diagrams help the practitioner to uncover the underlying structure of the system.

3. Overview of Relevant Learning Curve Theory

The organizational learning curve was first explored by Wright[7] who observed that unit labor costs in air-frame fabrication declined with cumulative output. The general form of the learning curve model[8-10] is presented in Eq.(1):

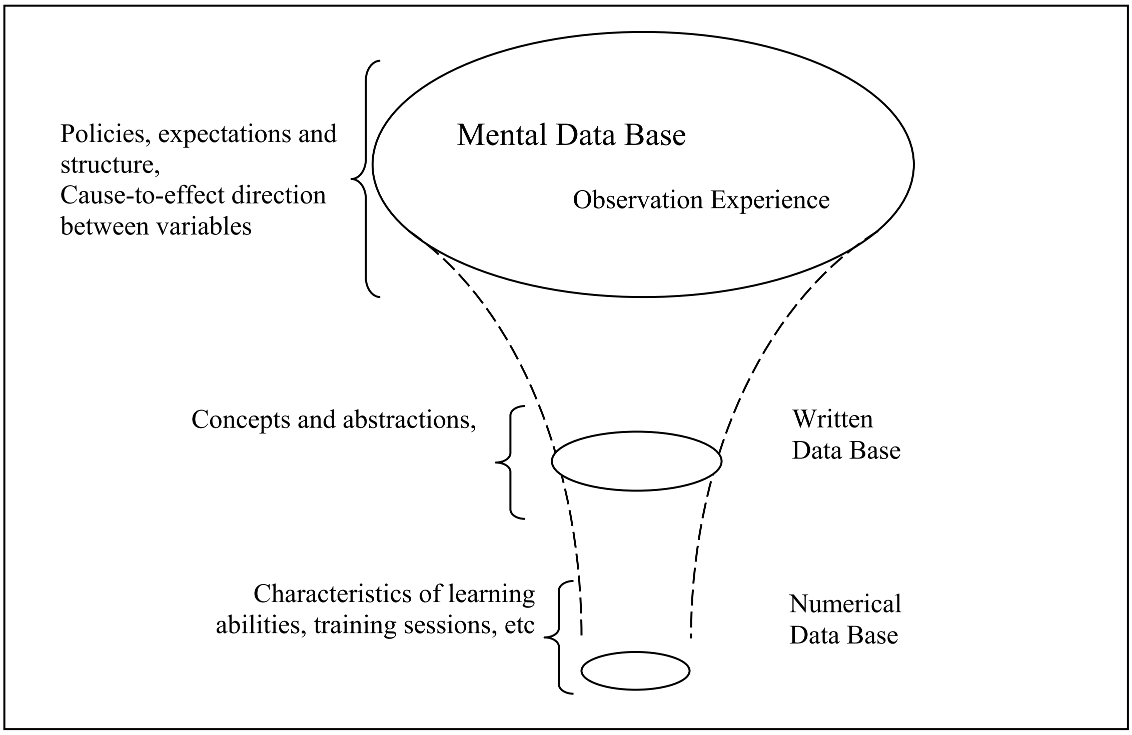


Fig. 4. Mental Data Base and Decreasing Content of Written and Numerical Data Bases

$$T_N = T_{Initial} \times N^b$$

and

$$b = \frac{\log(\theta)}{\log 2.0} \quad (1)$$

where

T_N = time requirement for the Nth unit of production
$T_{Initial}$= time requirement for the initial unit of production
N = number of completed units (cumulative production)
θ =learning rate expressed as a decimal

Argote and Epple[31] stated that organizational forgetting, employee turnover, transfer of knowledge across products and organizations, incomplete transfer within organizations, and economies of scale are factors that produce variability in learning curves across organizations.

Wyer and Lundberg[32, 33] propose that the learning curve slope is affected by the amount of planning put forward by management. Adler and Clark[34] propose a model that focuses on single traditional experience variables and double-loop learning; two key managerial variables (engineering change and training).The authors conclude that the learning process can vary significantly between departments and that learning can be concentrated in both labor-intensive and capital-intensive operations.

Adler and Clark[34] posit that the "human learning process model begins with the relationship between experience and the generation of data driven by that experience." As more data are generated, it is processed by the organization leading to the creation of new knowledge, which in turn leads to a change in the production process. Part of this new knowledge directly affects single-loop learning based on repetition and on the associated incremental development of expertise. This learning helps workers or direct laborers to be more efficient and efficacious at their jobs. The remaining generated knowledge will affect the double-loop learning process (effectiveness).Here, the learning takes place in the management environment, where decision rules, data interpretation and data generation are adapted to be in line with newly acquired knowledge to increment output. The authors caution that even though a double-loop learning model is certainly a facilitator of learning, it can disrupt knowledge either temporarily or permanently depending on management's understanding of the learning system. It is worth noting that Adler and Clark's model is consistent with Sterman's[1] double-loop learning model.

Formal training and equipment replacement illustrate how managerial decision making can be improved due to a better understanding of past behavior[35] as a result of double-loop learning. Training time should lead to improvement in worker performance concluding that experience is also affected by training. Learning in management is prompted by the problems encountered throughout the production process. The new policies generated by management should result in improved productivity.[34]

3.1. *Adaptation Function Learning Model*

The planning process can be improved through a better understanding of how the individual worker, as well as the firm, have historically adapted to past learning situations. Furthermore, the lack of a goal seeking behavior in traditional learning curves is not realistic.[36]

The adaptation function mathematical model is presented in Eq. (2).

$$Q(q) = P\left[1 - e^{-(a+\mu q)}\right] \quad (2)$$

where
Q(q) = the rate of output Q after q units have been produced
P = desired rate of output
a = initial efficiency of the process
μ = process rate of adaptation = *f(y1, y2, y3, ...,yn)*
q = cumulative number of units produced

"We suggest that the firm's cumulated experience or stock of knowledge on a particular job at a specified time can be summarized in the stock of the product it has produced up to that time. Thus, as the firm produces more and more of a given product, it increases its stock of knowledge on that product and is able to come closer to the desired rate of output[8]." The model assumes that there is a known, or expected, level of performance *P*. It also assumes that the process will start at an unwanted or initial rate of output *Q(q)*.As *q* starts to increase, *Q(q)* will approach *P* at a rate determined by a and μ.Levy suggests that the initial efficiency of the process a is an estimation of the amount of training provided to the worker as well as the preparedness of the system to start the new process. The process rate of adaptation μ is a function of different y variables that influence the rate at which an organization can learn. The process rate of adaptation then is influenced by the experience the worker has in similar job functions. That is, the more experienced a worker is, the faster he/she will be able to identify problems with the process and find solutions. With that, Levy suggests that learning can happen in three different ways: autonomous learning planned or induced learning, and random or exogenous learning. Induced learning is influenced by pre-planning activities such as mock runs, pre-production models, tooling determination, etc, and by industrial engineering tools such as time and motion studies, and control charts after the process starts. Random or exogenous learning happens when the form gains knowledge of the process from unexpected sources such as new materials characteristics, suppliers, government, etc. Finally, autonomous learning happens as the worker gains more experience with the actual process and identifies ways to improve or make more efficient his/her tasks

3.2. *Adaptation Function seen from a System Dynamics Perspective*

Levy's adaptation function[8] introduces a goal-seeking behavior to the learning curve body of knowledge. Eq. 2 generates an exponential growth behavior until the rate of output reaches the desired level. If we substitute q for t(cumulative time), express the desired rate of output as percentage of errors per day and invert the behavior (by adding $e^{-(a+\mu q)}$ instead of subtracting) towards exponential decay (in order to minimize errors per day), an exponential decay function is created (Fig. 5).

4. Transition-Phase Management Model Development

The behavior over time graph representation of the adaptation function can be translated into a system archetype (Fig. 5).The 'balancing loop' archetype is the best representation of this goal seeking behavior (Fig. 6) where the action causes the current state to move towards the desired state.

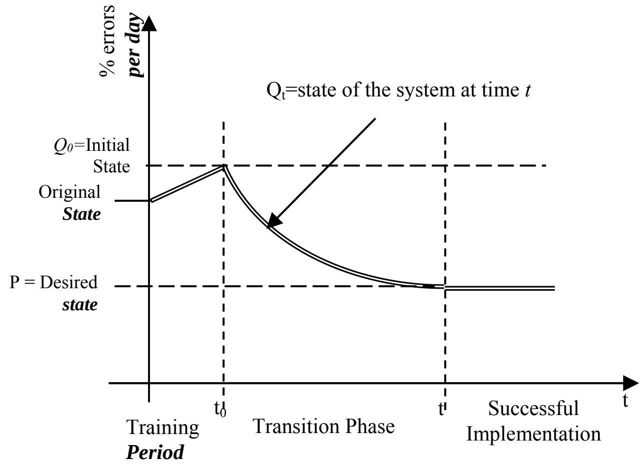
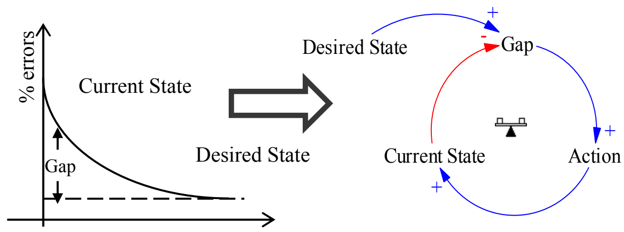


Fig. 5. Levy's Adaptation Function adapted as behavior



over time graph[2]

Fig. 6. Behavior over Time Graph and Balancing Loop Causal Loop Diagram[2]

At first glance, the 'balancing loop' appears to be a good fit to the behavior over time shown in Fig. 5. However, in reality a transition-phase will not occur without glitches or inconsistencies. For instance, the balancing loop ignores the effects of factors like forgetting, employee absenteeism, and different levels of experience, varying learning abilities, pressure to manage resources, and pressure to complete the project on time.[36]

The 'drifting goals' archetype can model the pressure generated by any deviations from the original plan, which may result in changes on deadlines, or target state. Fig. 7 presents the 'drifting goals' archetype using causal loops.

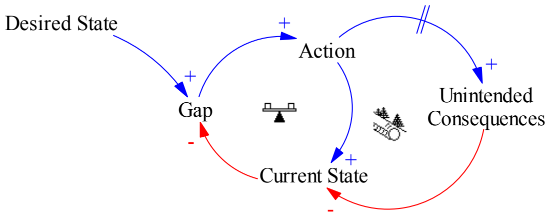


Fig. 7. Drifting Goals Archetype and Behavior Over Time Graph[2]

Notice how the lack of convergence from the current state concerning the desired state generates pressure to adjust either the target percentage of errors per day or the deadline.

On the other hand, the current state may differ from the desired state due to errors in planning that cause unintended consequences. The 'fixes that fail' archetype represents this problem context. Fig. 8 presents the 'fixes that fail' archetype in causal loop format.

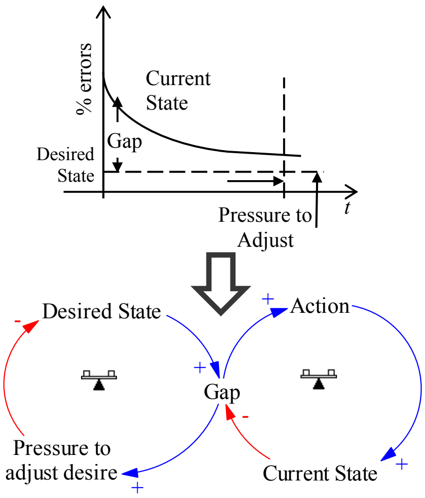


Fig. 8. Fixes that Fail Archetype[2]

The drifting goals and fixes that fail archetypes provide more complete solutions than the balancing loop archetype alone. However, if used separately they provide an incomplete solution (Fig. 9).

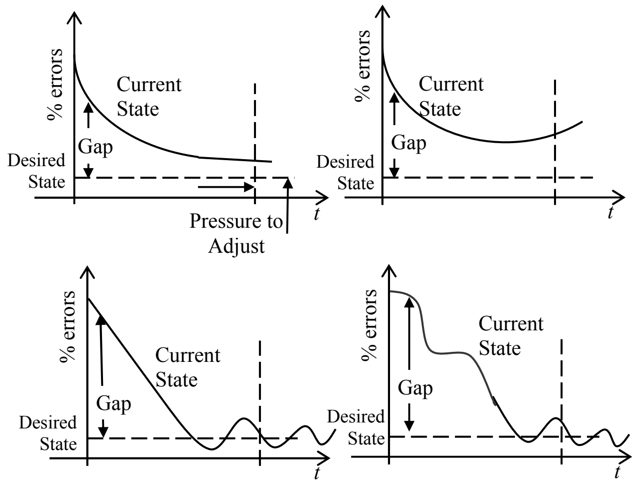


Fig. 9. Individual behavior over time graphs by drifting goals and fixes that fail archetypes[2]

The solution to the problem is to combine the 'balancing loop' with the 'drifting goals' and 'fixes that fail' archetypes into a meta-archetype. This new structure is called the adaptation function causal loop.

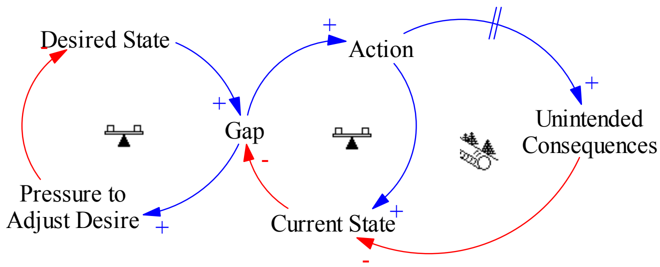


Fig. 10. Adaptation Function Archetype[2]

The adaptation function causal loop introduces the generalized structure that a transition-phase management system dynamics model should follow to replicate the behaviors over time as presented in Figs. 3-9. In it, the current state is influenced by an action, that in Levy's terms[36] are: the initial efficiency of the process *'a'* defined by initial and ongoing training and organizational culture; and the process rate of adaptation *'µ'* affected by individual employee learning rates, employee level of experience, and frequency of practice (mean time between entries).To fit Eq.2, Fig. 10 is adapted as follows:

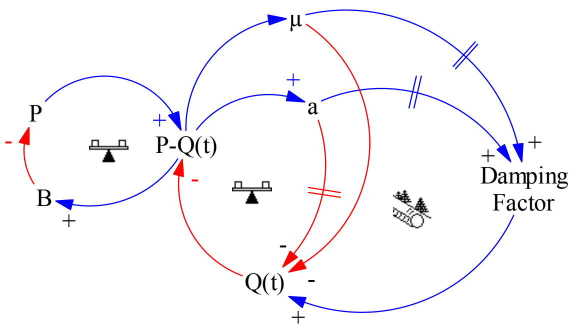


Fig. 11. Transition-Phase Management Model Causal Loop Diagram[2]

Fig. 11 shows three types of adaptation processes. The first one is planned or induced learning that impacts directly the potential efficiency of the process. The second one is random or exogenous learning, resulting from information received about the process that could not be anticipated or planned for and it impacts the process rate of adaptation. The third type is autonomous learning, which results from planning and on-the-job learning mitigating the effects of unintended consequences.

Based on Fig. 11, it is possible to infer that the less the firm plans (efficiency of the process -*a*) the bigger the gap will be and so the larger the unintended consequences. Therefore, factors that can be controlled before the new process implementation (and that are endogenous to the organizational structure) such as training, business seasonality, organizational culture and technology available, determine the efficiency of the process.

The process rate of adaptation μ, is composed of variables that affect the process during the implementation such as learning ability, employee's experience, and education. That is, the faster the organization adapts to changes, the smoother the implementation will be (it reduces the oscillation) and the faster the percentage of errors per day will converge to the desired state.

Autonomous learning is, a result of the efficiency of combining the process and the process rate of adaptation.[36] Autonomous learning will be considered as negative unintended consequences or damping factors *F*; that is, the less autonomous learning there is, the larger the effect of the unintended consequences will be.

The causal loop diagram presented in Fig. 11 transforms into the main model structure (stock and flow diagram) as presented in Fig. 12. The mathematical form of the transition-phase management model is presented in Eq. 3.

$$Q_t(t) = \int_0^t [F(s) - a(s) - \mu(s)]ds + Q_0 \qquad (3)$$

where

Q_t = percentage of errors per day

Q_0=Percentage of Errors per Day as a result of initial training

a = initial efficiency of the process = *f(organizational culture, training. time)*

μ = process rate of adaptation= *f(experience, learning ability, feedback, time)*

F = Damping Factors = *f(a, μ, forgetting)*

and

$$P = \int_0^t B(s)\, ds + P_0; where$$

P_0 = intial desired percentage of errors

$$B = \text{Pressure to Adjust P}$$
$$= f(|P - Q_t|, time) \begin{cases} 0 \; if \; |P - Q_t| \to 0, regardless \; of \; t \\ \geq 0 \; if \; |P - Q_t| > 0 \; and \; (t_f - t) \to 0 \end{cases}$$

Transition-Phase Management Model Sub-structures Development

Development of the substructures a, μ and F in the model requires the development of operational definitions for each factor present in Eq. 3. Each factor is evaluated, based on their operational definition, in accordance to a general rubric as presented in *Table 1.*

Table 1. General Rubric to Evaluate Factors

Grade	1	2	3	4	5
Meaning	Very Poor or non-existent	Poor	Average	Above average	Superior or excellent

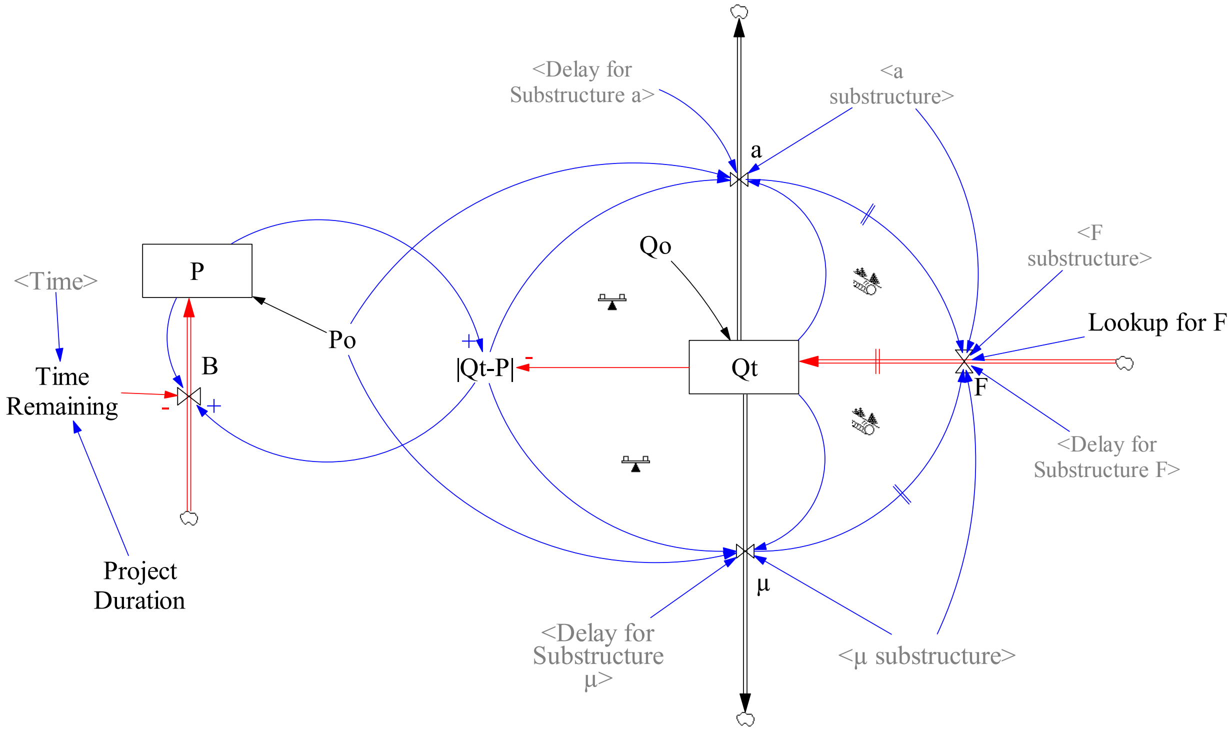


Fig. 12. Stock and Flow Diagram for Transition-Phase Management

Managers wishing to evaluate their organization's capacity to implement a new process need to grade each one of the factors in accordance with their operational definitions as suggested in the general rubric. Grades do not have to be integers.

4.1.1. *Efficiency of the Process Substructure*

The efficiency of the process substructure *a* contains the factors that have affect the efficiency of the organization to implement new processes. The factors were validated from Levy's proposed factors[36] and complemented after informal interviews with healthcare managers. The efficiency of the process substructure determines the magnitude of its impact to the current percentage of errors per day Q_t and specifies the delays resulting from the factor's values. Fig. 13 presents the resulting structure:

Adequacy of Technology in Company. This factor identifies how efficient, efficacious and effective is the current technology (computing, software, communications) with regards to the company's operations. For instance, a grade of 1 may indicate that not even the most basic tasks are supported correctly by the current technological standards. A grade of 3 may indicate that there is room for improvement, but all basic operations are satisfied with current standards. A grade of 5 may indicate that all technology is state-of-the-art and the company is leader in operations and standards.

Adequacy of Technology for Project. This variable identifies how efficient, efficacious and effective is the current technology (computing, software, communications) with regards to the proposed new process requirements. For instance, a grade of 1 may indicate that not even the most basic tasks would be supported correctly by the current technological standards. A grade of 3 may represent that there is room for improvement, but all basic operations would be satisfied with current standards. A grade of 5 may indicate that all technology is state-of-the-art and the company is a leader in operations and standards.

Training Frequency. Training frequency refers to how often training sessions are held. A grade of 1 represents a daily training schedule.2 represents a 3-day a week training schedule, 3 represents 2-days a week training schedule, 4 represents 1-day per week training schedule, and5 represents less than one day a week training schedule.

Training Duration. Training duration refers to the length of each training session. A grade of 1 represents a session shorter than 1 hour, 2 represents a session of 1 hour, 3 represents a session of 1.5 hours, 4 represents a session of 2 hours, and 5 represents a session longer than 2 hours.

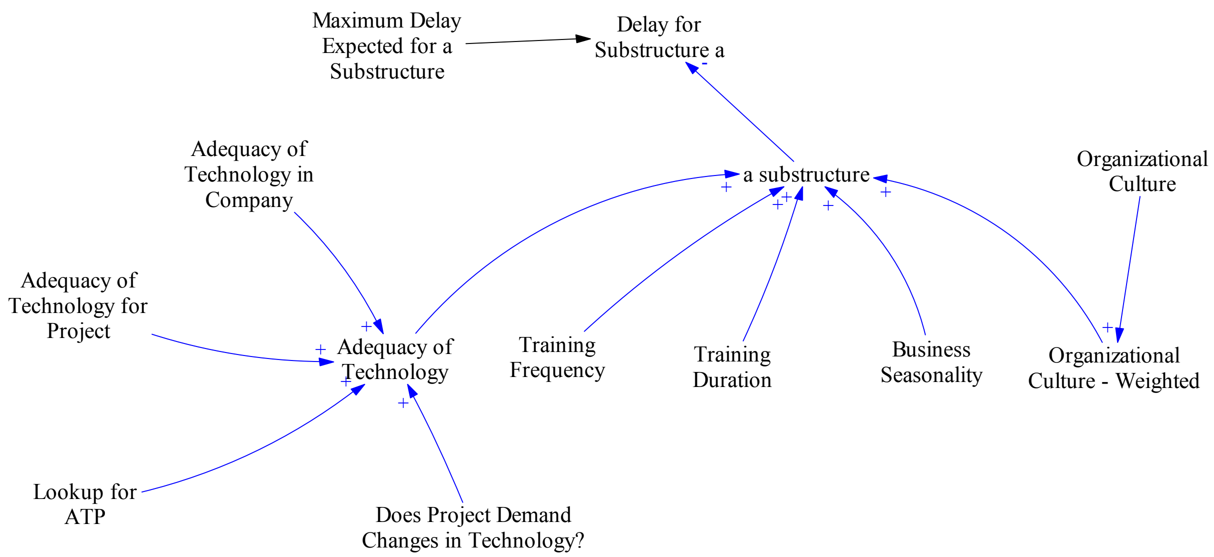


Fig. 13. Efficiency of the Process Sub-structure

Business Seasonality. Business seasonality refers to the state of the business cycle for a healthcare provider, i.e. if it is flu season, budgeting season, etc. A grade of 1 refers to a very busy business cycle (i.e., flu season, financial reports) and a grade of 5 represents a slow business cycle (meaning priority can be placed to the new process implementation).

Organizational Culture. Organizational culture refers to the flexibility and organizational climate in the organization with respect to new process adoption. A grade of 1 represents a very poor organizational culture and a grade of 5 indicates excellent organizational culture.

Maximum delay expected. Managers should make an assumption as to what they expect to be the longest delay that could be caused by the factors within the structure.

Does the Project Demand Changes in Technology? This factor does not mean the changes will be made, it only considers whether a change is required. This is a binary grade factor where a grade of 0 means the project does not require a change and a grade of 1 means the project does demand a change in technology. An example would be if the new process requires the use of tablets and wireless communications and the organization does not possess tablets and/or the current technology does not support wireless communications.

4.1.2. Process Rate of Adaptation substructure

The Process Rate of Adaptation substructure μ includes the factors that have an effect on the process rate of adaptation to implement new processes. The factors were selected in accordance with mental data bases (see Figure 12) after informal interviews with healthcare managers. It is worth noting that in independent interviews, managers listed the same factors.

The process rate of adaptation substructure is designed to calculate the magnitude of its impact to the current percentage of errors per day Q_t and to determine delays resulting from the factors values. Fig. 14 presents the resulting structure.

Feedback Turnover Time. Feedback turnover time refers to how long does it take for the implementation team to address inquiries from end users (expressed in days).This is an estimation that has to be made with the best knowledge available. The rubric is not required for this factor.

Implementation Team Effectiveness. This variable measures how experienced, cohesive and dynamic the implementation team is. It is measured with respect to the expected impact it can have on the transition phase. A grade of 1 represents a very poor or negative impact and a grade of 5 represents an excellent positive impact.

Staff Learning Rate. Staff learning rate refers to the overall learning ability of the staff. A grade of 1 represents very poor learning rates and a grade of 5 represents excellent learning rates. It is expressed as an average of all involved staff in the new process operations.

Communication Skills. Communication skills refer to the organization's personnel ability and willingness to communicate with each other. A grade of 1 represents very poor communication skills and a grade of 5 represents excellent communication skills.

Staff Experience. Staff experience refers to the level of experience that the staff possesses both in professional jobs and in a job related to their current one. A grade of 1 indicates no at all and a grade of 5 indicates a high level of relevant experience.

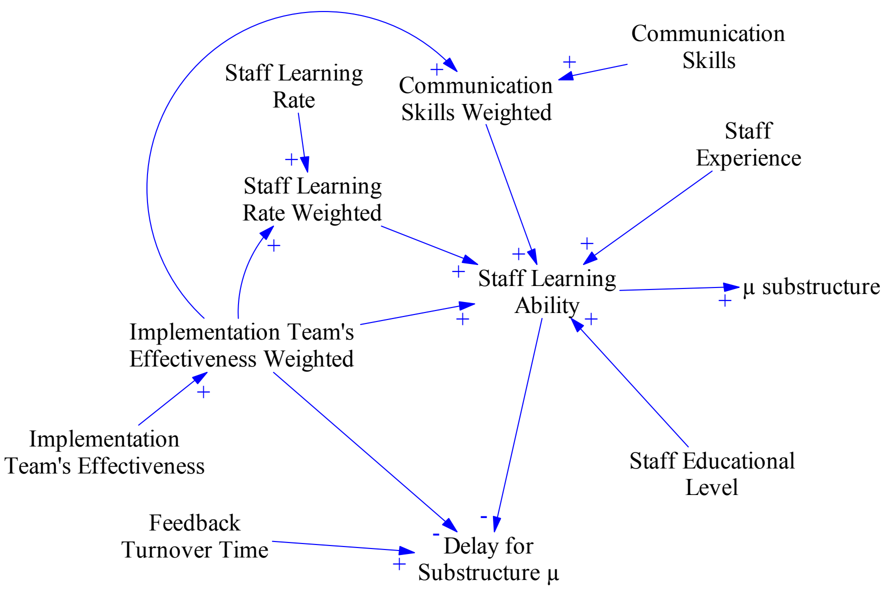


Fig. 14. Process Rate of Adaptation Sub-structure

Staff Educational Level. Staff educational level refers to the minimum and maximum academic levels achieved by the staff. A grade of 1 indicates incomplete K-12 education. A grade of 5 indicates graduate degrees.

Feedback Turnover Time. This variable refers to the expected normal time to receive, acknowledge and resolve issues. It is expressed in days.

4.1.3. Damping Factors Substructure

The Damping Factors Sub-Structure (*F*) calculates the magnitude of unexpected consequences based on the existence of standard operating procedures (SOPs) and the effect of forgetting. In the main structure it reacts to the values generated by the efficiency of the process and process rate of adaptation sub-structures (Fig. 10).

Forgetting. It is an estimation of the percentage of training and process details expected to be forgotten by the process users.

Existence of SOPs. A grade of 0 represents no presence of SOPs for the new process. A grade of 1 represents the existence of SOPs for the new process.

All factors were determined using as mental database[14] created from interviews with the managers and by identifying the five Ms+E (Measurements, Materials, Personnel, Environment, Methods and Machines) from Ishikawa's fishbone diagram[15] and adapting them to the particular activities within a healthcare environment. The written database results from the literature review validated the observations from the managers and their interpretations of Ishikawa's five Ms+E.

5. Model Validation – Simulation

In this section, a sensitivity analysis is presented by varying the ranges of inputs of different sets of variables and to all input variables at once and their effects on the initial state Q_0, current state Q_t, gap $|Q_0-P_0|$, all efficiency of the process a factors, all process rate of adaptation μ factors and damping factors F to verify and validate the model. *Table 2* presents a relation between the parameters being tested and the corresponding Figure, according to the function employed.

The tests were performed using the built in sensitivity analysis of Vensim® Professional software. Each parameter possible value is explored either using a uniform or a triangular distribution. The uniform distribution was selected due to the non-existence of previous data, thus leading the researchers to assume that all states have the same probability of happening. The triangular distribution was selected to test how robust is the model to biasing. 10,000 replications were conducted for each sensitivity test using both distributions independently. A time frame of 90 days was set.

Table 2..Relation of Validation Tests, Parameters and Corresponding Figure

Test #	Parameters	Figure	
1	P_0 and Q_0	13	Uniform Distribution
2	All sub-structures factors	14	
3	All sub-structures factors, P_0 and Q_0	15	
		16, 17, 18,19	Triangular Distribution
4	Pessimistic scenario with all sub-structures factors set at 1	20, 21	
5	Moderate scenario with all sub-structures factors set at 3	22, 23	
6	Optimistic scenario with all sub-structures factors set at 5	24, 25	

5.1. *Extremes tests*

In this section, Figs. 15 to 17 show the results of sensitivity analysis by testing the model throughout its extreme values. The tests serve to investigate if the model behaves in unexpected ways, and, as can be observed, it does not. It is important to emphasize that these tests serve to verify and validate the model. Policy related tests will be developed at a later stage using an action research approach.

Notice that when all parameters are set to a moderate scenario and both the initial and desired states are tested, the expected behavior from the theoretical model shows an increase in variation but still converges to the desired state with a minimal effect on the pressure to adjust the goal. That means that the model is somewhat sensitive to changes in initial conditions, but will eventually smooth them out. In addition, it can be observed some pressure to adjust the goal is present, a behavior that arises when oscillation is high when helping $|Q_0-P_0|$ reach a value of *0*.

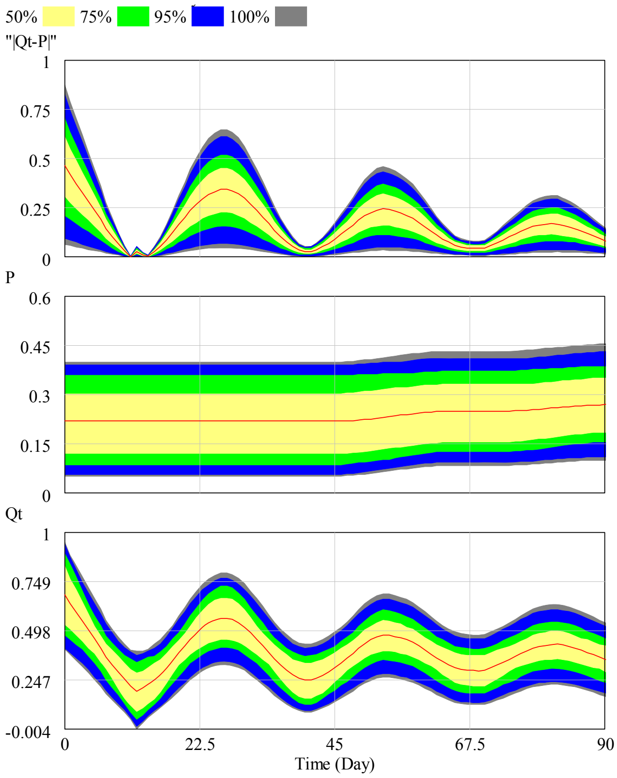


Fig. 15. Sensitivity analysis varying P_0 and Q_0 using uniform distribution.

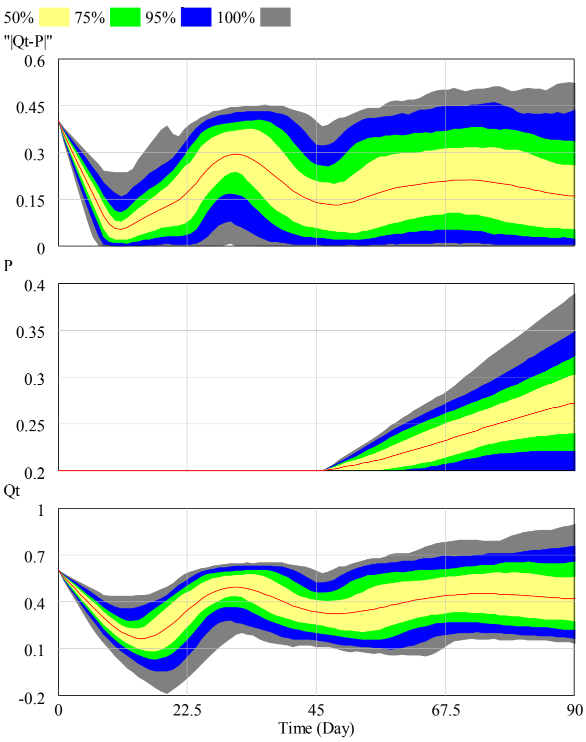


Fig. 16. Sensitivity analysis varying all factors in substructures.

Notice how when all factors are randomly varied, the distribution of possible outcomes becomes wider and the pressure to adjust the goal *P* is incremented substantially. In this test it is possible to observe that all possible behaviors that the model can generate are consistent with the theoretical model presented in section 3. That is, if all or most of the factors adopts pessimistic values, the model exhibits growing oscillation, or if they are set to an optimistic scenario convergence happens quickly with little to no oscillation. The center line indicates the average of all 10,000 runs.

In Fig. 17 all factors, plus P_0 and Q_0, are varied throughout the whole range of values in accordance to the theoretical model depicting all possible values the model can generate. The model showed no undesired behavior.

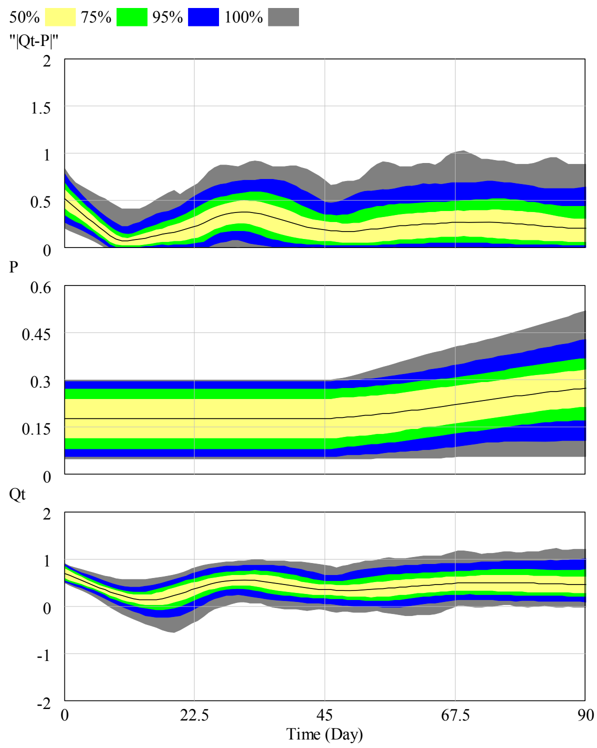


Fig. 17. Sensitivity analysis varying all factors in substructures and P_0 and Q_0 using a random uniform distribution.

Figs. 18, 19, 20 and 21 illustrate the way the model behaves under different sets of scenarios. Figures 17 to 27 explore in more detail the boundaries of the model.

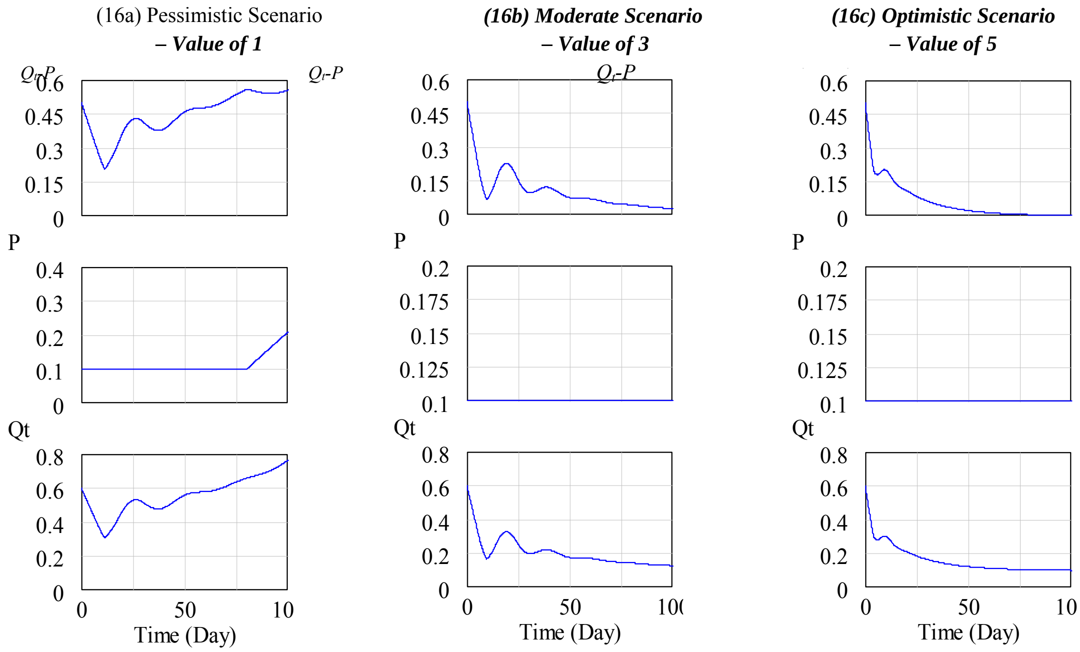


Fig. 18. Discrete analysis setting all factors in to a pessimistic (a), moderate (b), and optimistic (c) scenarios with P_0=*10%* and Q_0=*50%*.

5.2. *Substructures effect on* Q_t

In this section a sensitivity analysis varying separately the factors of each structure is presented to understand and validate the effects of each structure on the model. We first consider the *a* substructure.

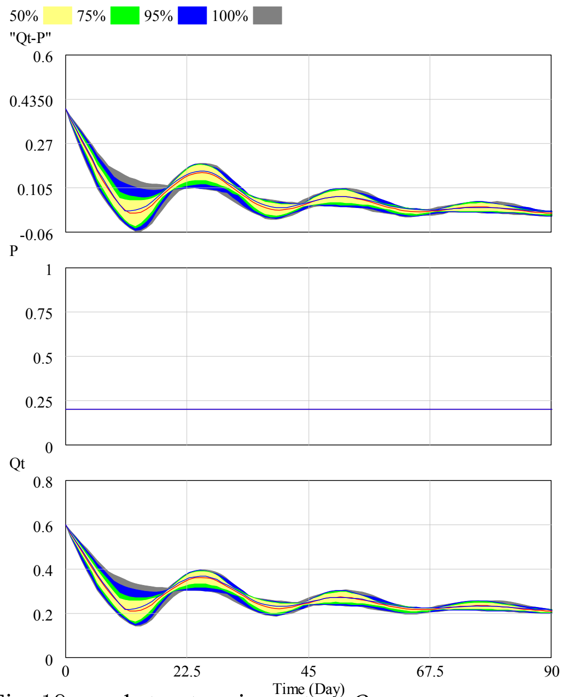


Fig. 19. *a* substructure impact on Q_t

Notice how the lack of preparation (training) creates larger oscillations in the process. Depicted below in Figure 20 is the impact of the μ substructure on Q_t and P.

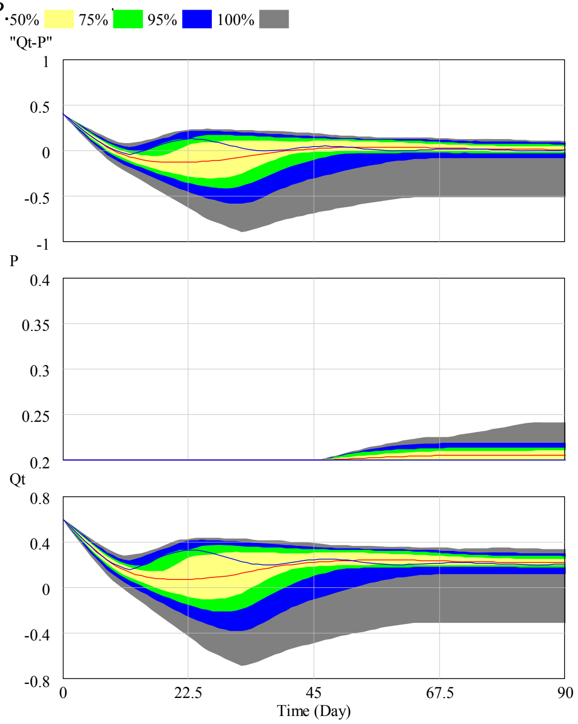


Fig. 20. μsubstructure impact on Q_t

The μ substructure produces amplitude in the efficacy of the implementation of the new process. Depicted below (Fig. 21) is the impact of the μ substructure on Q_t and P.

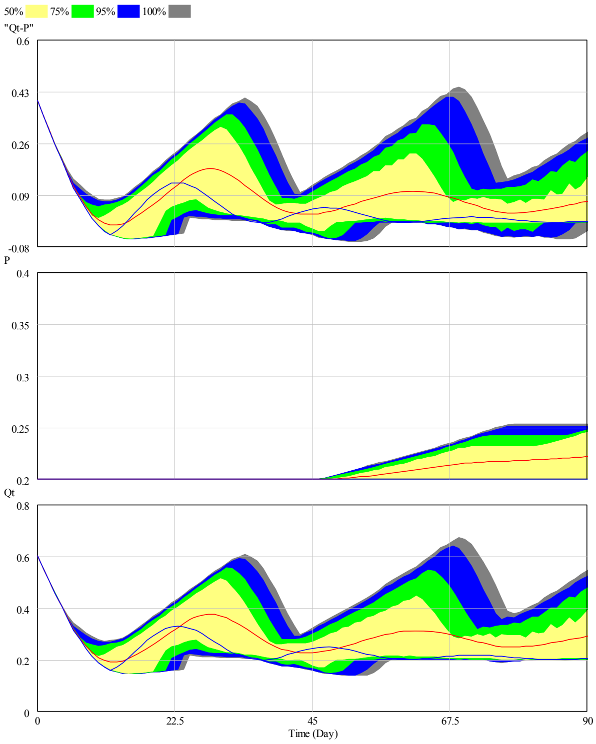


Fig. 21. *F* substructure impact on Q_t

Figs.18-21 demonstrate that *a, μ*, and *F* substructures have an effect on the percentage of errors per day Q_t. Note that if there is an increase in *P* it means that *B* is having an effect as a result of the goal $|Q_t\text{-}P| \rightarrow 0$ failing to be met, therefore inducing pressure to adjust the goal.

5.3. ***Bias analysis***

Next, sensitivity simulations using triangular distributions were used to vary the factor values in accordance to a pessimistic, moderate and optimistic scenario are presented.

Figures 22 and 23 portray a sensitivity analysis with a bias towards a pessimistic scenario using a triangular distribution while Figs. 24 and 25 a moderate scenario and Figs. 26 and 27 an optimistic scenario.

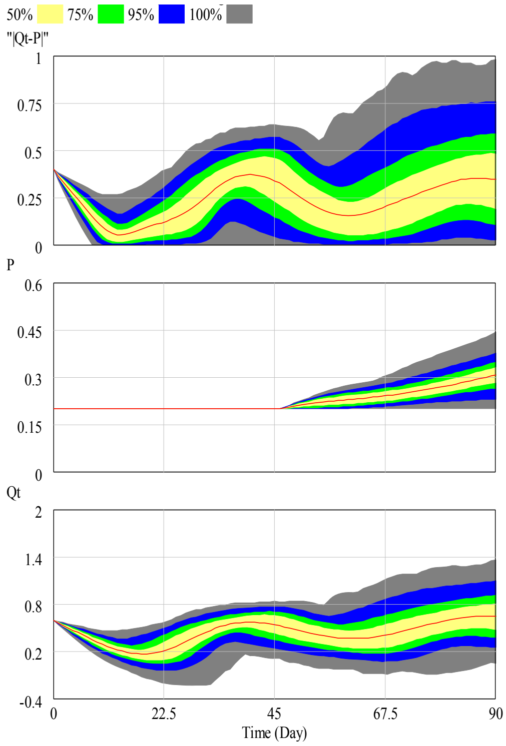


Fig. 22. Sensitivity analysis using triangular distribution with peak set to pessimistic scenario varying all factors in substructures (value of 1).

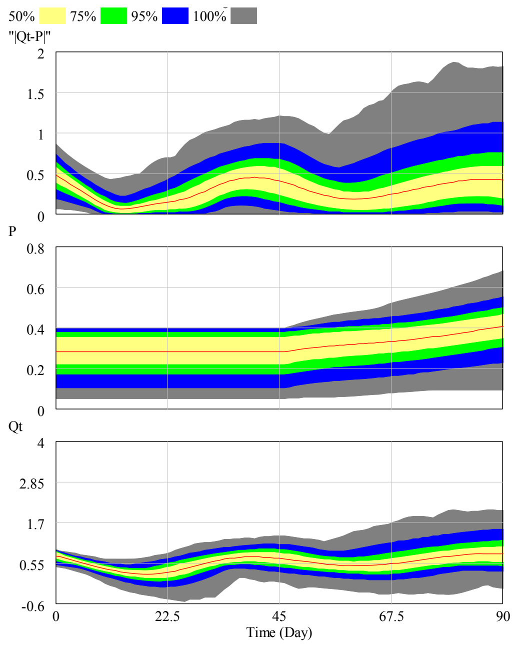


Fig. 23. Sensitivity analysis using triangular distribution with peak set to pessimistic scenario varying all factors in substructures (value of 1) plus varying P_0 and Q_0.

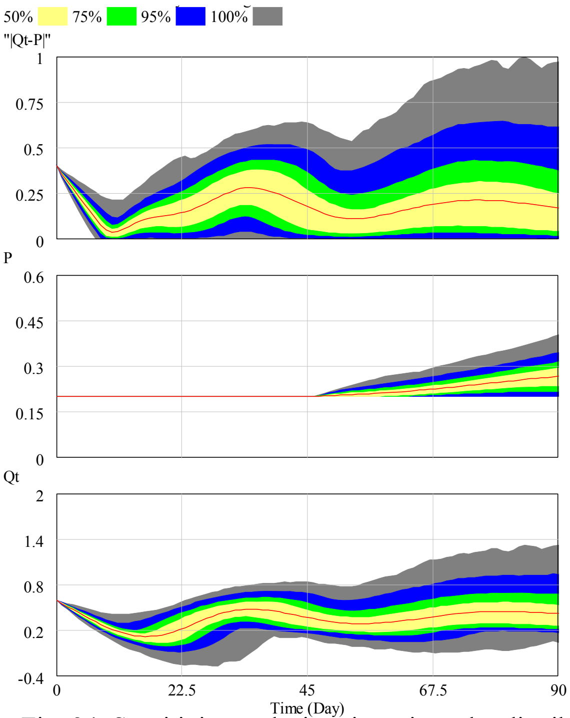


Fig. 24. Sensitivity analysis using triangular distribution with peak set to moderate scenario varying all factors in substructures (value of 3).

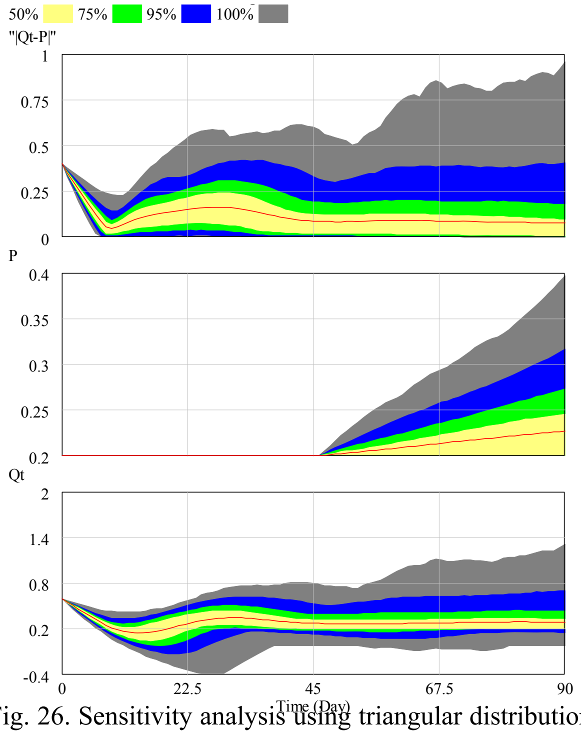


Fig. 26. Sensitivity analysis using triangular distribution with peak set to optimistic scenario (value of 5)

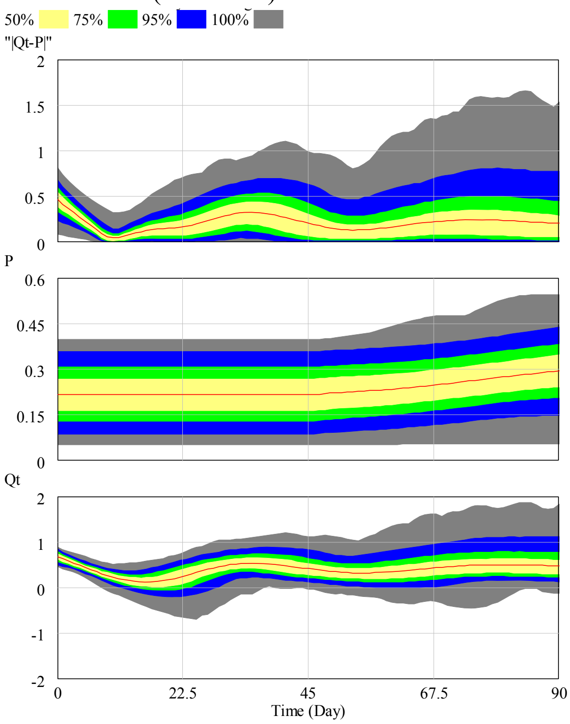


Fig. 25. Sensitivity analysis using triangular distribution with peak set to moderate scenario varying all factors in substructures (value of 3) plus P_0 and Q_0.

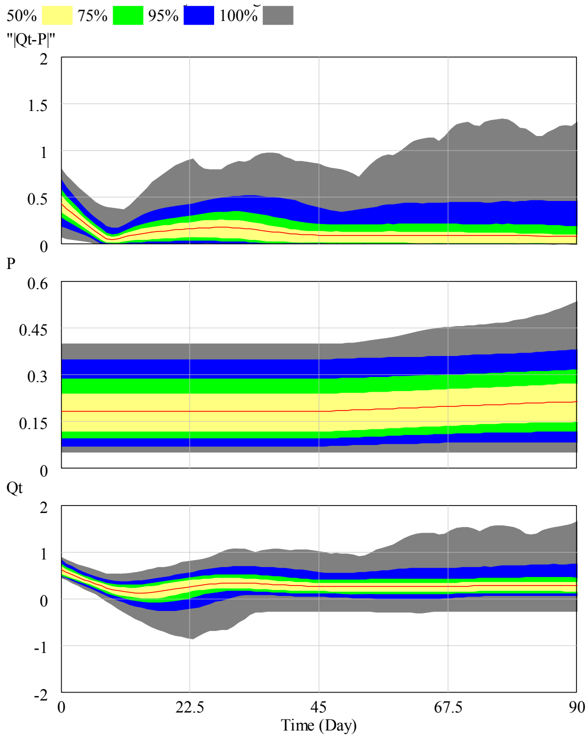


Fig. 27. Sensitivity analysis using triangular distribution with peak set to optimistic scenario (value of 5) including P_0 and Q_0.

6. Conclusions and Future Work

The adaptation function provides a goal seeking mechanism to model organizational learning. It is however, limited in the amount of dynamic behavior it can capture. A system dynamics model to model a transition-phase, illustrated in a healthcare setting in this paper, was developed as a system dynamics model using the concepts of the adaptation function as a foundation, then verified and validated. The model shows it is apt at modeling the dynamic behaviors that may arise during a transition-phase.

By repeatedly using this model, managers will learn about their organization by following a double-loop learning process as portrayed by Sterman[1] using an action research approach. The results from the sensitivity simulations are encouraging. The model behaves according to theory[2] and is capable of forecasting different behaviors arising from all possible factors combinations.

The model still requires testing in real life projects, in varying contexts besides healthcare such as lean and six sigma implementations in manufacturing, to better assess its accuracy and reliability. For that, future work will focus in the application of the model in projects that present different completion lengths and differences between Q_0 and P_0 ($|Q_t$-$P_0|$).Furthermore, managerial implications regarding policy assessment and policy optimization will be explored using an action research framework as presented by Calvo-Amodio[37].

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