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EMBEDDING ANALYTICS IN BUSINESS PROCESS MANAGEMENT: A KNOWLEDGE-BASED APPROACH DRIVEN BY QUALITATIVE SYSTEM DYNAMICS MODELING

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ABSTRACT

This study aims to examine how system dynamics modeling approach can be employed when implementing business process changes and associated performance improvements with embedded analytics. As cited in the literature, most IT implementations are prone to many unexpected operational failures such as resistance to change, resistance to knowledge codification, political agendas, organizational culture, trust concerns, disregarding end-user needs, issues resulting from hasty deployment of applications, among others. Accordingly, the goal of the study is to develop a conceptual model to capture the interactions among variables in the IT implementation domain. The model will help detect unforeseen outcomes that have the potential to derail the successful implementation of business process changes early on, and hence can prevent unintended consequences becoming dominant over time due to iterative reinforcing behavior.

Keywords: business process management, system dynamics modeling, analytics

INTRODUCTION AND LITERATURE REVIEW

The literature cites many studies where business process improvement, business process reengineering, and business process management (BPM) (Rummler, Ramias and Rummler, 2010) projects were attempted and yet not all implementations can be considered successful. Given the fact that business process changes require simultaneous adjustments to the supporting IT infrastructure and application systems, IT researchers continuously investigate the attributes that will increase the odds for a successful implementation. These include investigating the nature of knowledge work in business processes so that appropriate knowledge representation strategies can be devised to tackle the knowledge characteristics. Considering the extent of knowledge intensiveness as a continuum, the routine tasks can be supported by relatively simple computer code since the knowledge content is fully structured, whereas the challenging decision tasks require embedding appropriate levels of analytics as part of process design changes in order to provide the needed decision support capabilities. However, the effort required to support relatively complex decision tasks needs to be commensurate with the expected benefits given the challenges in structuring knowledge in knowledge intensive application domains. A knowledge-based (KB) approach requires capturing expertise of knowledge workers using artificial intelligence knowledge representation schemes such as rules, semantic nets or frames. Moreover, organizations can supplement process changes by incorporating a range of analytical models (Davenport, Harris and Morison, 2010; Laursen and Thorlund, 2010; Sabherwal and Becerra-Fernandez, 2011; Glaser, J. and C. Salzberg, 2011) that can monitor performance levels. Similarly, knowledge-based reasoning can be employed to analyze the results of these models (in conjunction with other relevant data) to trigger appropriate responses such as notification of related parties or further analysis. Thus, coordination of organizational activities can be facilitated and enhanced by incorporating analytical models during business process design efforts.

Systems Dynamics modeling aims to improve decision making by explicitly representing the interactions among decision variables and uncovering the underlying assumptions by questioning beliefs. Hence, system dynamics modeling can facilitate creation of new knowledge when building knowledge management systems (KMS), including knowledge-based applications, to improve process efficiencies and effectiveness. As Senge (1990, *page xix*) states "*Developing explicit system models of complex issues, both conceptual models and formal computer* *simulations to test alternative policies and strategies, strikes many action-oriented managers as too theoretical. This is especially troubling in light of the widely recognized difficulties that afflict so many American corporations in transferring learning from one group to another. 'No theory, no learning,' Deming used to say. If we cannot express our assumptions explicitly in ways that others can understand and build upon, there can be no larger process of testing those assumptions and building public knowledge."*

This study aims to examine how system dynamics modeling approach can be employed when implementing business process changes and associated performance improvements with embedded analytics. As cited in the literature, most IT implementations are prone to many unexpected operational failures such as resistance to change, resistance to knowledge codification, political agendas, organizational culture, trust concerns, disregarding end-user needs, issues resulting from hasty deployment of applications, among others. Accordingly, the goal of the study is to develop a conceptual model to capture the interactions among variables in the IT implementation domain. The model will help detect unforeseen outcomes that have the potential to derail the successful implementation of business process changes early on, and hence can prevent unintended consequences becoming dominant over time due to iterative reinforcing behavior.

The literature cites the significance of learning (Argris and Schon, 1978) from past experiences and structuring this knowledge so that it can be applied to current problems. Organizations can utilize the explicit knowledge that is available in company artifacts or learn/create new knowledge. The creation of new knowledge requires the codification of tacit knowledge (Nonaka, 1994; Nonaka and Hirotaka,1995). Tacit knowledge refers to past experiences and assumptions of organizational members and needs to be explicated and structured prior to reuse by others.

Based on literature, there are two types of learning (Fiol and Lyles, 1985; Argyris and Schon, 1978; Senge, 1990). Single-loop (first-order or lower-level) learning evaluates the organization's outputs (e.g. performance), and if goals are not met, recommends taking corrective action. Most business process management (BPM) metric is based on single-loop (first-order) learning and focuses on measuring results, usually referred as KPI's (Key Performance Indicators). In contrast, double-loop (second-order or higher-level) learning questions the existing decision processes (decision variables, criteria, objective functions/goals) and their underlying assumptions (Senge and Sterman, 1992), and hence aims to gain insight and capture the domain interactions. System Dynamics modeling provides double-loop learning and facilitates creating new knowledge. Knowledge reuse improves decision making and process efficiencies, and in turn lowers transaction costs (Walsh and Ungson, 1991).

Since semi-structured problems exhibit choosing appropriate actions to alter the resource (such as personnel, money, material, customer) levels that are not at desirable points (such as bottlenecks, capacity constraints, quality), it is likely that an action that change one resource may adversely impact the other resources. Given the difficulties in predicting the outcome, alternative solutions can be evaluated including embedding analytics to decision processes. Second and higher order effects of these decisions are difficult to envision and may be addressed qualitatively to some extent and may require a simulation study to understand the full impact over time due to the unpredictable nature of the dominant forces over time. Simply focusing on BPM metrics is a short-term" quick-fix" approach which may result in unintended consequences due to complex interactions among decisions/policies and their impact on other resources/metrics. Hence, the paper emphasizes the role of systems thinking in process change efforts rather than focusing solely on performance measures or technology.

PROPOSED APPROACH

The study explores the role of a conceptual modeling approach based on qualitative system dynamics modeling in understanding the domain interactions and underlying causes of outcomes in IT implementations in process management context, along with the identification of decision processes that can benefit from knowledge-based solutions (such as routinized use of knowledge-based rules) or analytical solutions.

The following figure depicts a qualitative system dynamics causal loop diagram, representing the relationships between variables. The arrows indicate a causal relationship between variables. A positive (+) causal relationship indicates that both variables change in the same direction (i.e., an increase (decrease) in one variable results in an increase (decrease) in the other variable. Whereas, a negative (-) causal relationship indicates that an increase (decrease) in one variable causes a decrease (increase) in the other variable (Vennix, 1994). For example, an increase (decrease) in "Problems with Business Process Management (BPM) or lack of Knowledge-Based Rules or lack of Analytics" may increase (decrease) the number of "Quick Fix" initiatives. The feedback loops can be negative (-), *balancing*; or positive (+), *reinforcing*. Balancing loops indicate that the system is exhibiting a goal-oriented behavior and hence has a stabilizing structure. The positive loop reinforces the process and amplifies the impact of the initial change. For example, an increase in addressing the problems with short-term "Quick Fix" approaches decrease the resources needed for "fundamental solutions ", which in turn amplifies the need for more "Quick Fix" solutions; and overtime may become a dominant force. In turn, increase in "Quick Fix" solutions may cause incompatible system solutions and/or IT implementations failures. Thus, qualitative system dynamics models can be used in assessing business process changes and understanding related IT implementation issues.

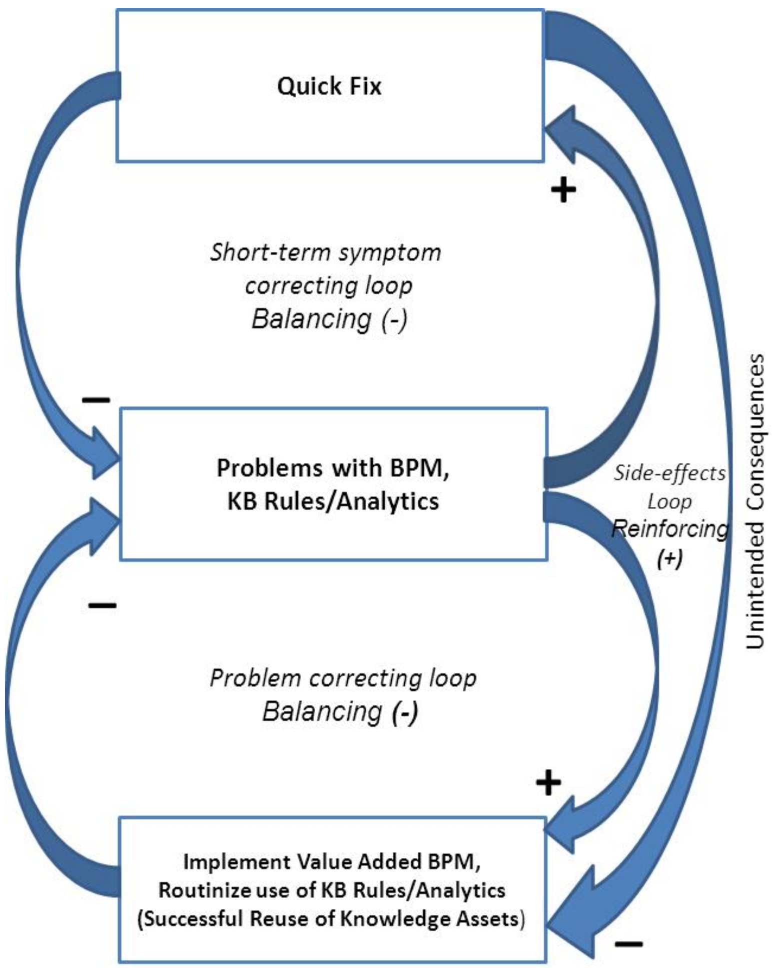

Figure 1. Systems Dynamics Modeling

ILLUSTRATIVE EXAMPLE

We introduce typical business processes and the relationships among them using a case study from the insurance industry domain (reported in Senge and Sterman, 1992; Senge 1990). Additionally, Hammer and Champy (1993) provides insurance industry examples. Other researches also refer to examples in insurance domain (Rosenberger et al., 2009, Binbasioglu et al., 1996 and Yu et al., 1996). We use these examples to show the limitations of focusing solely on performance metrics; and rather highlight the importance of understanding application domain dynamics for fundamental solutions. Since the qualitative system dynamics approach uncovers the *relationships* among different metrics and the underlying reasons why such results are attained, it can be used as part of process improvement efforts when assessing the likely impact of process change efforts on other measures. Quick-Fix solutions include basic process improvements or determining KPIs or technology choices for data collection/representation/analytics. At best, investments in these components will offer partial solutions in the short run. However, funds and effort employed for piecemeal solutions will decrease the capacity to invest in long-term fundamental solutions; and promote and reward an organizational culture which value more short-term focus. Furthermore, Quick-Fix approach increases the probability to choose wrong performance measures or policy changes; which in turn has the potential to become a dominant force overtime and may result in unintended consequences. This is a critical difference between a Quick-Fix approach and a system dynamics modeling approach which guides the process by uncovering likely impacts among measures/policies.

In the insurance claims processing domain, typical BPM metrics focus on results such as settlement amounts, litigation costs, delays in settlements or speed of settlement, employee turnover, among others. These measures are based on single-loop (first-order) metrics and help understand the company performance. However, basic BPM metrics do not provide insight why those results are achieved and the relationships among the performance indicators.

Senge and Sterman (1992) models the insurance claims processing domain as a system dynamics model; their research discusses insurance domain relationships, including potential unintended consequences, together with the results of simulation runs in order to assess the long-term impacts and dominant factors.

Summarizing Senge and Sterman (1992), the following are the relationships among key measures and policies when *expediting settlement of insurance claims,*

- Lower level of settlement amounts leads to dissatisfied customers.
- Unhappy customers are likely to litigate, which then will significantly increase the cost, and requires case specific details.
- Lack of adequate documentation negatively impacts the litigation success.
- Documentation of case details requires time and effort, and in turn increases cost and delays settlements.
- Focusing on speed of settlements, unfavorably impacts the documentation; and may result in additional cost when customer chooses to litigate.
- Faster settlements do not allocate sufficient time to examine the case, or to communicate with the customer, or to document case details.
- Intense work pressure causes work related stress and employee burnout, which may lead to turnover.

- When there is employee turnover, availability of adjusters will be decreased, which in turn reduces the available time per claim.
- Hiring new adjusters may not immediately decrease the need for more adjusters since new adjusters need to be trained; usually resulting in reduced adjuster capacity.
- The company must have the financial resources to be able to hire new employees.
- Fair settlement amounts may likely improve customer happiness;
- Customer happiness is likely to lower litigation cost and litigation staff; and may likely lead the company to retain or grow the customer base.
- Quality claims processing and related documentation require considerable workforce capacity who can devote adequate time to claims processing.

For example, as highlighted above, "time", as a measure, provides limited insight in *expediting settlement of insurance claims*. The measure is meaningful when interpreted in conjunction with other relevant factors including customer happiness, employee turnover, litigation cost and duration, among others.

The following list suggests how processes can be augmented with decision analytics tools and/or process activities can be restructured.

- Analysis of the speed of processing claims on employee turnover.
- Analysis of the speed of processing claims on litigated cases versus the availability of associated documentation.
- Analysis of the speed of processing claims on customer base (retain/growth).
- Analysis of past customer claims when detecting fraud.
- Analysis of settlements in terms of paying off the customer claim versus offering a settlement.

In addition to determining suitable choice of analytic tools, system dynamics modeling can help identify which processes can benefit from other knowledge assets. For example, the steps involved in processing claims can be categorized and linkages among different policies can be established including exceptions. Further, advanced systems with build-in knowledge-based components can be used to streamline basic process activities and to incorporate analytic tools as needed.

CONCLUDING REMARKS

The proposed approach extends the IT implementation literature by employing a qualitative model to understand the domain dynamics for achieving successful use of knowledge assets that can be integrated as part of value-added Business Process Management. Discovering the nature and extent of routine use of knowledge-based rules as well as performance measures and analytics would be of interest to both researchers and practitioners when implementing process changes

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