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REA Ontology-Based Simulation Models for Enterprise Strategic Planning

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ABSTRACT: In this paper we propose REA ontology-based simulation models to facilitate firms' strategic planning processes. Managers often must assess complex business environments, changing competitive forces, and uncertain futures, and then make significant resource allocation decisions. Traditional quantitative planning and budgeting techniques often fail to consider nonlinear relationships, discontinuities, and uncertainty. Qualitative techniques can lack rigor and perpetuate biases. Using simulation modeling technology could specifically address those concerns, but there are few if any general simulation models of integrated business processes to support strategic planning processes. Basing simulation models for enterprise planning on the REA framework, an established enterprise domain ontology, would facilitate reuse of and learning from these models in a variety of business contexts. An ontology-based planning model would allow managers to assess the consequences of alternative resource allocation decisions and determine appropriate performance indicators. To illustrate the concepts, we provide an example of how that model could be used to facilitate management planning.

Keywords: REA framework; ontology; simulation models; strategic planning systems.

Data Availability: Not applicable.

I. INTRODUCTION

In this paper we examine the potential contribution of modeling and simulation technology to firms' strategic planning processes. We further propose the use of the REA framework to guide the development of that technology. Today's managers must often assess complex business environments, changing competitive forces, and uncertain futures, and then use their judgment to make significant resource allocation decisions. Over 50 years ago, Simon (1957) described such managers as boundedly rational; they are limited in ability to process information and solve complex problems. Thus, although strategic planning requires managers' judgment, that judgment can be flawed. Modeling and simulation technology offers a potentially valuable tool to assist managerial decision-making and reduce potential biases (e.g., Greasley 2004; Sterman 2000).

Firms' strategic planning includes two parts: (1) strategy formulation, and (2) strategy implementation (e.g., Anthony 1965; Kaplan and Norton 2004; Anthony and Govindarajan 2004). In the strategy formulation part, managers decide on organizational goals and the general strategies to achieve those goals. In the strategy implementation part, managers develop programs that will achieve the firm's goals efficiently and effectively (Anthony and

Govindarajan 2004). We focus primarily on the strategy implementation part of the strategic planning process, wherein managers perform the analyses necessary to decide on strategic initiatives and corresponding capital investments given the overall objectives of the firm.

During the strategy implementation phase, most firms still use traditional capital budgeting techniques, such as net present value (NPV) or internal rate of return (IRR), to make capital investment decisions (Graham and Harvey 2001). Table 1 summarizes the prominent strategic planning and capital budgeting techniques. These techniques work well for individual projects with well-defined costs and benefits, but Kaplan and Norton (1996) argue that these traditional techniques create barriers that limit managers' ability to assess the cumulative impact of cross-functional strategic initiatives or interrelated investments, such as a major information systems investment. Furthermore, traditional techniques may not adequately incorporate risks and uncertainties and the value of options (Fabozzi et al. 2008). A number of researchers therefore advocate the use of real options techniques to consider uncertainty and the value of abandoning, deferring, or expanding projects (e.g., Accola 1994; Arya et al. 1998; Childs et al. 1998; Amram and Howe 2002). Yet, advanced quantitative techniques such as real options analyses remain limited in their ability to consider nonlinearities and incorporate qualitative factors (e.g., Drew 2006). Additionally, real options analysis is no better than traditional techniques in ability to assess cumulative impacts of strategic initiatives.

One tool, scenario planning, allows managers to combine information from multiple sources and consider the interactions of alternative investments under uncertainty. Scenario planning[1] combines traditional analytical methods with management judgment and opinion to analyze multiple views and different perspectives on the future (Schwartz 1996; Senge 1990). It can include such unstructured approaches as storytelling and strategic conversation. Although managers are expected to develop and consider a variety of reasonable alternative scenarios (e.g., Schoemaker 1995), scenario planning has been criticized for a lack of rigor (Miller and Waller 2003). Scenario planning relies on management judgment, but it can also perpetuate managers' cognitive biases (Lovallo and Kahneman 2003). Nevertheless, scenario planning is now widely-used—the Bain & Company 2006 annual management tools survey indicates that over 70 percent of their respondents report the use of scenario planning for investment decision.

A number of firms have recognized that scenario planning can lack rigor and produce flawed decisions. Since 2001, firms have increased the number of analytical tools and the amount of technology applied to decision-making (Bain & Company 2003). Modeling and simulation technology supports scenario planning to improve decision quality, reduce cognitive biases, as well as provide a related benefit of educating participants in the decision process (Paul et al. 1999; Greasley 2004). Modeling and simulation promotes a deeper understanding of the modeled processes, helps articulate goals, and fosters a culture of measurement (Greasley 2004). Morecroft (1999) argues that the process of model building provides much of the value for management, since it allows managers to visualize the strategy. Then, simulation allows managers to rehearse the strategy visually and mentally, and perhaps avoid discovering costly errors only after changes are implemented.

Conversely, modeling and simulation can entail substantial costs, since managers and developers must first document and model business processes for each strategic initiative to be evaluated. In this regard, simulation developers face common enterprise systems

[1] Scenario planning is also called contingency planning.

TABLE 1
Comparing Strategic Planning/Strategy Implementation Techniques

Approach	Advantages	Disadvantages	References[a]
Traditional capital budgeting techniques, such as: Net present value (NPV) Internal rate of return (IRR) Profitability index (PI)	Consider cash flows of the project Consider time value of money Incorporate risk through cost of capital Useful in selecting projects when capital is rationed	Require estimates of cost of capital Estimates of cash flows based on assumptions about the economy, competitors, consumer tastes, construction costs, etc. Fail to consider range of alternative scenarios Treat projects in isolation Fail to consider qualitative benefits/costs Typically ignore value of options to abandon, defer, or expand investment	Various managerial accounting texts, e.g.: Bamber et al. 2008; Fabozzi et al. 2008;
Real options analysis	Supplements traditional capital budgeting techniques to consider values of options to abandon, defer, or expand project	Same as for NPV, IRR, PI except for ignoring value of options May require complex option valuation models	Fabozzi et al. 2008; Accola 1994; Arya et al. 1998; Childs et al. 1998; Amram and Howe 2002;
Sensitivity analysis	Analyzes the sensitivity of project value to assumptions about cash flows and risk for different possible future scenarios	Same general problems as underlying technique to which sensitivity analysis applied Requires assumptions about likely future scenarios Focuses on one change at a time; becomes unmanageable when considering two or more factors in combination	Fabozzi et al. 2008; Bamber et al. 2008; Barnes, Jr. 1984; Smith 1994;
Monte Carlo simulation	Allows consideration of multiple factors simultaneously	Still treats projects in isolation Requires assumptions about likely future scenarios and probability distributions	Fabozzi et al. 2008; Greasley 2004; Anthony and Govindarajan 2004;

(*continued on next page*)

TABLE 1 (continued)

Approach	Advantages	Disadvantages	References[a]
Scenario planning	Explores the joint impact of multiple uncertainties Can consider the interaction and integration of multiple projects Applies management judgment to limit the number of scenarios Incorporates techniques to address expected managerial cognitive biases, e.g., overconfidence, under- and over-prediction of change, search for confirming evidence Process supports management learning	Relies heavily on management judgment to assess potential outcomes of scenarios Time consuming to develop, prepare, read, and revise scenario plans and related analyses Better suited to consideration of broad directions than for specific strategic initiatives; may not result in rigorous evaluation of individual initiatives Often lacks feedback loop to learn from prior decisions	Schoemaker 1995; Drew 2006; Mason 1969; O'Brien 2004; Klayman and Schoemaker 1993; Schwartz 1996; Senge 1990;
Simulation models	Provides same benefits as all techniques listed above Visual decision aid addresses managerial cognitive biases Provides immediate feedback on likely decision outcomes Can tie to organization's measurement system to learn over time	Relies on management judgment to determine the scenarios considered, probability distributions, etc. Requires design, development, and implementation of potentially complex computer-based business process simulation models Requires investment in developing managerial expertise in the use of models	Dutta 2001; Winch 1998; Sterman 2000; Morecroft 1999; Ziegler et al. 2000; Greasley 2004; Paul et al. 1999; Richmond 1997;
Ontology-based Simulation models	Provides same benefits as simulation models Offers an accepted model as the starting point for applying management judgment Supports model reusability and adaptability	Disadvantages of simulation models remain although ameliorated	Silver et al. 2006; Fayez et al. 2005; Benjamin et al. 2006; Linthicum 2004; Geerts and McCarthy 2000a, 2000b; Church and Smith 2007.

[a] Example references, not intended to be an exhaustive list of all relevant articles or books.

development problems, such as lack of standardized terminology and lack of shared understanding among users from various organizational units. Recently, researchers have begun to advocate the use of ontologies to address those development problems (Paul et al. 1999; Benjamin et al. 2006; Silver et al. 2006). Ontologies provide a formal specification of the concepts and relationships that can exist for an agent or a community of agents (Gruber 1993). Thus, they enable knowledge sharing and information integration and provide a consistent basis for understanding and communicating domain phenomena (Paul et al. 1999).

An ontology-based approach to model and simulation development establishes a standard semantic structure, and more importantly facilitates reuse of these models in a variety of scenario-planning contexts. Established models could be updated over time to address new scenarios or reevaluate existing scenarios. The standard semantic structures would allow integration of models. The use of an ontology should therefore reduce costs of both development and use, as decision makers become familiar with a consistent decision aid that can be utilized repeatedly. Paul et al. (1999) argued that the development of a specific process ontology could be the single most important advance to (1) promote the use of modeling within organizations, and (2) contribute to a better understanding of business process management issues.

We advocate the use of the resource-event-agent (REA) framework as an enterprise domain ontology, i.e., a standard semantic structure, for simulation models of enterprise processes. We select the REA framework as an enterprise domain ontology for several reasons. First, since the REA framework has been published in peer-reviewed accounting journals, it has undergone extensive analysis. It has proven to be a faithful representation of the objects and relationships between those objects that exist in the enterprise domain (e.g., McCarthy 1982; Geerts and McCarthy 1999, 2000b, 2002; Dunn et al. 2005). Second, the REA framework supports an integrated view of enterprise processes necessary to consider the cross-functional impact of major strategic initiatives (e.g., Church and Smith 2007). Third, the other potential ontology, the supply chain operations reference (SCOR) model, mentioned in existing simulation research, is not as extensive. The Supply Chain Council clearly states that the SCOR model does not encompass all business processes.[2]

We contribute to the design-science literature by extending the existing REA framework to a strategic planning context. Thus, the semantics of enterprise planning can be closely linked to those of enterprise operation. We show how the extended REA framework can facilitate the development of simulation models and thereby improve the application of technology to strategic decision-making. We also show how the nature of policy objects for simulation modeling to support strategy formulation differs from corresponding policy objects for management control. Although these are alternate views of the same enterprise policy objects, the simulation model objects address policy questions, i.e., *what could be*, while the management control objects address policy definitions, i.e., *what should be*. The use of the REA ontology facilitates simulation systems development, and ties the simulation model closely to existing enterprise policy and operations. Tying simulation models for strategy formulation to existing models for strategy implementation and operations allows tests of the strategy formulated from the simulation models and supports feedback to improve future strategic planning.

We proceed as follows. In the second section, we describe the strategic planning process and how modeling and simulation technology can support that process. In the third section,

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[2] See http://www.supply-chain.org/cs/root/scor_tools_resources/scor_model/scor_model.

we describe how ontologies support modeling and simulation. We also explain why we propose the use of the REA framework as an appropriate ontology for simulation. In the fourth section, we present extensions to the REA structures to accommodate simulation models for strategy formulation. In the fifth section, we offer a simple example using the extended REA framework to define a simulation model. We conclude in the sixth section.

II. STRATEGIC PLANNING PROCESS AND MODELING AND SIMULATION TECHNOLOGY

There is abundant literature describing processes for strategy planning (e.g., Anthony and Govindarajan 2004; Kaplan and Norton 2001, 2004). Managers make investment decisions and consider business process change based on enterprise goals and objectives. They base their plans on the expected impact of their decisions on enterprise performance, while also considering how changes in external factors, such as the general level of economic activity or the competitive environment, as well as the changes in internal factors, such as processes or products, will affect future performance.

Additionally, managers must consider process complexity and uncertainty. For example, projects may not be completed on time, competitors may react to product changes, the general economic conditions may change, and outcomes may depend on synergies delivered by other initiatives. Bounded rationality indicates that managers will not be able to anticipate and consider all the possible ramifications of their plans (Barber et al. 2003). Thus, managers often engage in an iterative process of resource allocation confounded by cognitive bias and organizational pressure (Noda and Bower 1996; Lovallo and Kahneman 2003).

To highlight the sources of biases, corresponding debiasing techniques, and the potential contribution of technology, we proceed by breaking the strategic planning process into a set of five linked conceptual elements. Together, these elements form a feedback loop that supports organizational learning (Senge 1990; Klayman and Schoemaker 1993; Kaplan and Norton 1996).

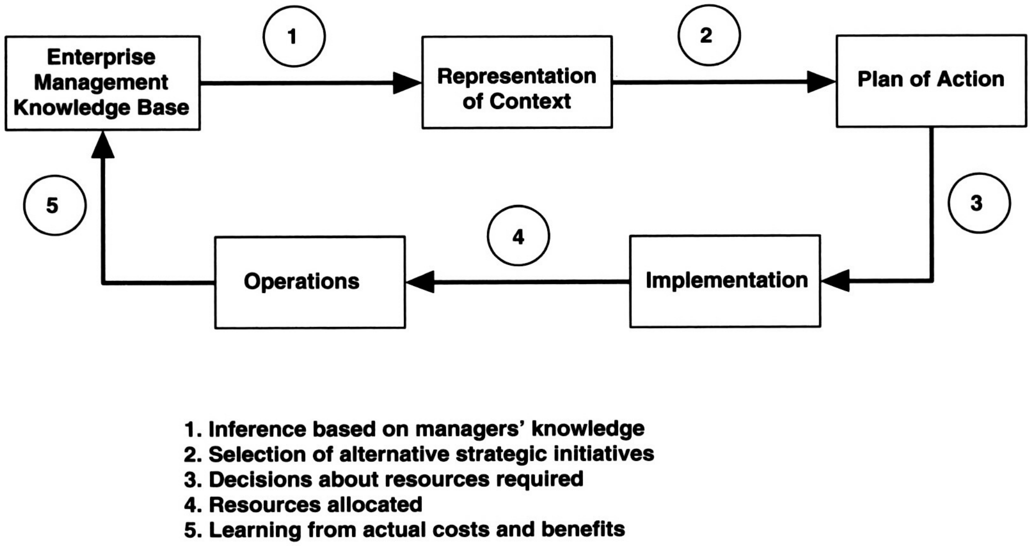
Elements of the Strategic Planning Processes and Potential Cognitive Bias

Figure 1 describes conceptual elements of the strategic planning process (adapted from Klayman and Schoemaker 1993). Starting from the top left, it describes (1) the enterprise management knowledge base, (2) the representation of context, (3) the plan of action, (4) implementation (of the changes related to a strategic initiative), and (5) operations of the firm after the implementation.

The *enterprise management knowledge base* consists of managers' tacit and explicit knowledge about the enterprise, its competitors, and its external stakeholders. The knowledge base includes managers' information about prior strategic initiatives and corresponding states of the environment from the firm's accounting and other information systems. Strategic planning involves the transfer of knowledge into plans and actions, so the knowledge base plays a fundamental role in quality of that process (Klayman and Schoemaker 1993). However, the knowledge base also reflects managers' beliefs and perceptions of their business reality, and so the knowledge base may be biased by overconfidence, a preference for confirming information, or framing biases (Lovallo and Kahneman 2003; Arnott 2006).

The *representation of context* reflects how managers define the strategic problems that they face. Since information about a (future) strategic context is never complete, managers must apply judgment based on incomplete information to define the problem and then develop appropriate alternatives to consider. At this point, managers' cognitive biases can

FIGURE 1
Conceptual Elements of Strategic Planning Process



adversely affect the decision-making process (Barnes 1984; Schwenk 1984; Klayman and Schoemaker 1993; Arnott 2006). For example, the framing of the problem affects how managers access their knowledge bases and can result in different and biased representations of the context (e.g., Kahneman and Tversky 1979; Barnes 1984; Lovallo and Kahneman 2003). Managerial overconfidence can limit the number of alternatives considered (Lovallo and Kahneman 2003). In the face of complexity, managers may resort to simplifying heuristics that can result in systematic errors in the selection and evaluation of alternatives (Das and Teng 1999).[3]

The *plan of action* flows from the context representation and results in resource decisions that depend on the alternatives considered and selected. At this point, firms typically apply various analytical techniques, such as NPV, IRR, and real options analysis, to evaluate various potential resource allocation decisions. Regardless of the capital budgeting techniques applied, managers' cognitive biases in context representation can result in inappropriate plans.

The *implementation* then reflects the firm's allocation of selected resources based on its plans. The firm incurs the initial costs of the resources, changes in systems, changes in processes, or other aspects of the investment. However, projects can fail either partially or completely, and the implementation may therefore differ from the plan.

Finally, the *operation* element involves the performance of business processes in the firm's competitive environment. The firm collects information about the process performance, which updates the *enterprise management knowledge base* and completes the feedback loop. However, it is often difficult to link operational performance to previous planning

[3] Arnott (2006) provides an extensive listing of cognitive biases in decision-making.

or resource allocation decisions, such as investments in information systems infrastructure (e.g., Bacon 1992). Thus, the feedback can be incomplete.

How Modeling and Simulation Technology Supports the Strategic Planning Process

As outlined above, the strategic planning process relies on managers' judgment, but that judgment can be biased. Modeling and simulation technology can help overcome potential biases and address business context dynamics and uncertainties. A model is a simplified representation of the actual business system intended to promote understanding (e.g., Maani and Cavana 2000). Modeling and simulation technology, then, represents the computer systems and practices necessary to prepare models of enterprise business processes and to test expected causal relationships in the model and display the results graphically.

To describe how modeling and simulation technology can support the strategic planning process, we refer again to Figure 1. The strategic planning process begins with managers' inference based on their knowledge. Managers abstract from their tacit and explicit knowledge to represent the strategic context as shown in Figure 1. To reduce the bias in this abstraction process, Fischoff (1982) describes several engineering strategies, including articulating of the problem, and decomposing the problem into understandable sub-problems. Thus, modeling the problem as it relates to the firm's business processes and value chain can reduce bias and facilitate management learning (Senge 1990; Morecroft 1999). Models can be decomposed into sub-models, e.g., of specific business processes, to highlight what is known and not known about the problem. A model allows managers to articulate, discuss, and reach consensus on expected causal relationships, thereby reducing framing bias (Hodgkinson et al. 1999).

Simulation tools then allow managers to run experiments with that model to answer "what if" questions. Simulation provides a rigorous approach that helps managers understand—and improve decisions about—complex business problems when experimentation with real systems is impractical (e.g., Sterman 1989; Oliva and Sterman 2001; Gary 2005; Forrester 1956, 1961). Thus, modeling and simulation technology supports a dynamic view of the business environment that enables managers to evaluate expected changes in those environments. Importantly, it sets the context for the strategic problem and requires managers to formalize their mental models of expected business process performance under a variety of reasonable scenarios. By forcing managers to clearly articulate expected business process behavior and the constraints on performance, modeling and simulation technology can reduce decision biases.

Once managers select alternative strategic initiates, number 2 in Figure 1, modeling and simulation technology further supports investigation of potential plans of action. Barnes (1984) advocates the use of sensitivity analysis and to highlight similarities to analogous situations to reduce cognitive bias. Modeling and simulation technology supports sensitivity analysis, and models based on business processes represent strategic problems in a familiar context. It allows them to reduce complexity in a consistent and structured manner, which also reduces potential bias (Ashton 1992).

Once managers decide on plans of action, modeling and simulation also supports implementation, since the models describe how the strategic initiatives should affect business processes and the simulations describe expected results (de Vreede and Verbraeck 1996; Paul et al. 1999). Modeling and simulation also helps define the process performance measures that will convey the benefits of the strategic investments, because managers must establish those parameters to evaluate the results of the simulation (Persson and Ohlnager 2002). Thus, it furthers comparison of actual to expected benefits, improving the link between plans of action and later operations.

III. ONTOLOGIES TO SUPPORT MODELING AND SIMULATION

Ontologies define the common words and concepts used to describe and represent an area of knowledge (Obrst 2003; Schreiber 2003; Linthicum 2004). Ontological theories impose order on domain phenomena by describing the structure of the domain and relations between objects therein (Weber 2003; Zuniga 2001). Thus, ontologies establish the architecture for the management information structures critical to the successful implementation of enterprise systems (Linthicum 2004; Uschold et al. 1998; Weber 2003). Domain ontologies support the sharing of concepts across functional boundaries and the reuse of those concepts in various applications (Geerts and McCarthy 1999; Benjamin et al. 2006; Silver et al. 2006).

How Ontologies Support Model and Simulation Development

Ziegler et al. (2000) contend that abstraction is key to constructing effective simulation models. The models must contain the essential, but sparse, set of entities and relationships that represent the real domain. The design and development of simulation models are facilitated when there are standard semantic structures for the underlying domain (Benjamin et al. 2006; Silver et al. 2006). Thus, a number of researchers now advocate the use of domain ontologies to facilitate the development of simulation models (e.g., Fayez et al. 2005; Dong et al. 2006). Managers could tailor generic, ontology-based, dynamic models to firm-specific situations and then use those models to formalize the expected impact of both qualitative and quantitative factors on business process performance. These models could be readily adapted to new investment strategic decisions and changing circumstances over time, mitigating the need to create planning tools for each strategic problem. Referring again to Figure 1, ontology-based modeling and simulation facilitates the *representation of context* in the strategic planning process.

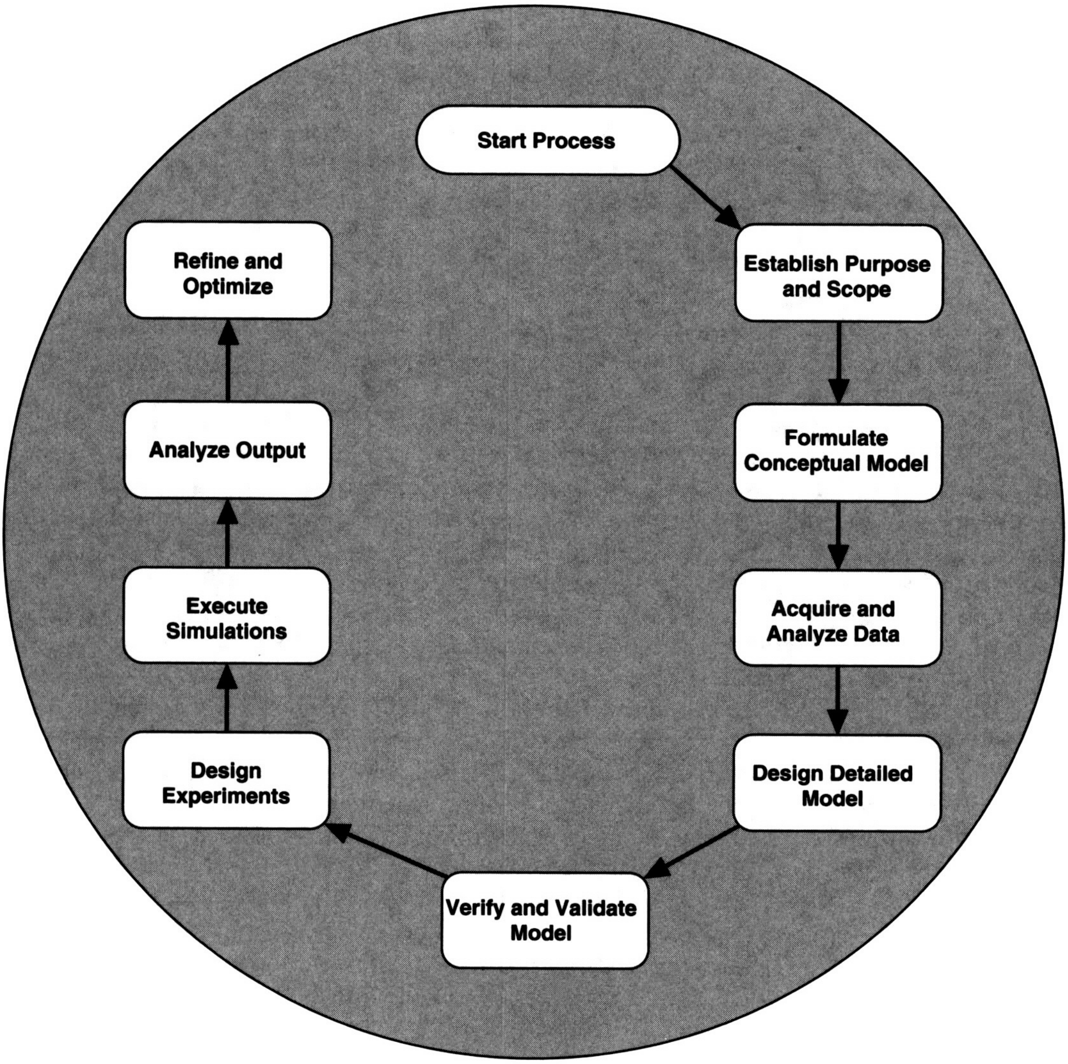
Like other enterprise applications, simulation requires a systems development process. Figure 2 describes a typical simulation development process (Benjamin et al. 2006), and Table 2 summarizes the contributions of ontology to each step of the enterprise simulation process. First, developers and managers establish the purpose and scope of the simulation. An appropriate ontology facilitates the determination of specific goals for the simulation based on the known demand for decision data in the domain (Benjamin et al. 2006).

Second, developers and managers formulate the conceptual model of the selected domain business processes. Since an ontology provides a common understanding of domain information structures, it facilitates the conceptual modeling (Silver et al. 2006). Reference to an appropriate standard also helps reduce managers' cognitive bias in representing the strategic context (Barnes 1984).

Next, developers and managers acquire and analyze data corresponding to the objects of interest in the domain, identifying essential characteristics, constraints, and associations. An ontology enables identification of appropriate data and data sources and helps specify the appropriate level of aggregation (Benjamin et al. 2006). It also helps managers organize their collective knowledge bases and bring the right knowledge to bear on the particular strategic problem (Klayman and Schoemaker 1993).

At that point, the developers and managers can complete the initial design of the detailed simulation model, establishing the expected behavior of, and associations among, domain objects. An ontology facilitates mapping real-world constraints into the behavior of abstract objects in the simulation models (Benjamin et al. 2006). In general, it supports the semantic information exchange that allows developers and managers to understand the

FIGURE 2
Business Simulation Process (Adapted from Benjamin et al. 2006)



fundamental nature of the underlying enterprise domain (Paul et al. 1999; Benjamin et al. 2006; Silver et al. 2006).

Developers, managers, and process experts then verify and validate the simulation model(s), iterating through the previous process steps until they achieve a valid model. After that, the managers and developers design appropriate experiments to address issues relevant to the intended planning decisions. The simulation models are then executed to analyze the dynamic changes in the business processes over time under various relevant scenarios. Managers analyze the results of the simulations, make their decisions, and/or further refine and optimize the simulation models.

TABLE 2
Ontology Contributions to Modeling and Simulation Process

Modeling and Simulation Process[a]	What Ontology Contributes to Process[b]	What the REA Ontology Further Contributes to Process[c]
Establish purpose and scope	Establishes consistent shared semantics; facilitates identification of domain decision requirements	Value chain and business process view of the enterprise tied to internal and external financial and operational reporting
Formulate conceptual model	Determines unambiguous abstraction levels; identifies appropriate objects and their roles; establishes systems constraints; defines object behavior and associations	Accepted semantic model that establishes expected resources, events, agents, and the relationships among them in the enterprise domain
Acquire and analyze data	Determines nature and source of data for models; defines levels of aggregation	Policy level and accountability level entities and relationships to identify sources of data in enterprise systems
Design detailed model	Facilitates detailed analysis of objects, object attributes, behaviors, constraints, and associations; allows interpretation of real-world process flow and decision logic	Detailed business process models as well as the enterprise-wide integration across processes; REA model that is easily understood by managers to facilitate input and communication
Verify and validate model	Establishes benchmark domain characteristics against which the structure of the models and expected flows of the simulation can be compared	Definition of process resources, events, and agents, and aggregation levels consistent with real-world accounting and process measurement requirements

(continued on next page)

TABLE 2 (continued)

Modeling and Simulation Process[a]	What Ontology Contributes to Process[b]	What the REA Ontology Further Contributes to Process[c]
Design experiments	Enables detailed identification of important objects, associations, constraints, and possible changes; maps real world constraints to simulation model constructs; links model outputs to domain decision requirements	Enterprise context that enables identification of appropriate objects linking to performance measures at all balanced scorecard perspectives as well as for financial reporting
Execute simulations	N/A	N/A
Analyze output	Facilitates the comparison of simulation output to corresponding domain objects and prior real world enterprise performance measures	Semantic link to accountability systems that captured prior performance
Refine and optimize model	Facilitates a shared understanding that allows managers to understand, combine, and refine models	REA model easily understood and used by managers

[a] Modeling and simulation process described in Benjamin et al. (2006).
[b] Ontology contributions from Benjamin et al. (2006), Silver et al. (2006), Paul et al. (1999).
[c] Contributions listed for REA Ontology from McCarthy (1982); Geerts and McCarthy (1999, 2002, 2006); Dunn et al. (2004); Gerard (2005); Church and Smith (2007).

The REA Framework as an Ontology for Modeling and Simulation

We argue that the REA framework provides a suitable—if not the most suitable—model of business processes to support strategic simulation models. The REA framework depicts business processes in terms of the events and related agents and resources (e.g., McCarthy 1982; Dunn et al. 2004). Implicit in the REA business process model of a company are its current strategic decisions. The choice of entities, relationships, and attributes reflect current and likely future information needs of the company given its current strategy. McCarthy (1982) presents the original REA framework as a general model of "the stock-flow aspects of accounting object systems" by characterizing accounting phenomena in terms of economic events and the associated enterprise resources and agents.

Although originally developed for designing accounting information systems, through ongoing research in the field of design science, the REA framework has been extended to specify broadly the set of objects and relationships among the objects that exist in the accountability infrastructure for an enterprise domain (Geerts and McCarthy 1999; Church and Smith 2007; Dunn et al. 2004). The REA framework has proven robust to critical analysis for over 25 years. Geerts and McCarthy (1999, 2000b, 2002) argue that the extended REA framework meets the definitions of an enterprise domain ontology; it supports an integrated view of enterprise processes.

Table 2 also summarizes how the REA framework could contribute to the enterprise simulation process. The REA framework is closely aligned with strategic theories that describe the enterprise in terms of business processes within a value chain (e.g., Porter 1985). Thus, the REA framework incorporates a widely accepted general model of the enterprise domain that can assist identification of decision requirements and allow managers to consider changes to their strategic objectives beyond that reflected in their current accounting model. Due to its origins as a description of accounting systems, the REA framework is also closely tied to enterprise financial reporting requirements, both externally and internally. Thus, the REA framework helps managers and simulation developers clearly articulate the purpose and scope of the simulation model(s).

The REA framework includes both policy and accountability level infrastructures that establish expected objects and associations within the domain, thereby facilitating conceptual and detailed modeling as well as data acquisition (Geerts and McCarthy 1999, 2002, 2006). The REA framework supports detailed business process models as well as enterprise-wide integration across processes (e.g., Dunn et al. 2004). Furthermore, the REA framework provides semantic links to elements of the enterprise domain essential to strategy implementation. For example, Church and Smith (2007) show that the REA framework broadly supports balanced scorecard information requirements, such as information about customers, competitors, and cross-process strategic initiatives. Thus, REA facilitates the identification of specific process performance measures consistent with balanced scorecard perspectives as well as standard financial reporting. Importantly, research shows that the REA framework is easily understood and used by managers (Gerard 2005). Thus, managers can use the REA framework to help design, verify, and validate detailed simulation models. Managers' participation in the model-building process further supports learning in the strategic planning process (Morecroft 1999).

Although the REA framework can contribute to the modeling and simulation process, it may not be the only appropriate ontology or the best. The most prominent competing model discussed in the simulation literature appears to be the SCOR (supply chain operations reference) model.[4] There are a number of articles that lay out the benefits of that model as an ontology for supply chain simulation (e.g., Fayez et al. 2005; Dong et al. 2006). We believe that prior research shows the REA ontology covers business processes represented in the SCOR model (e.g., Dunn et al. 2004; Church and Smith 2007). Thus, the benefits cited for the SCOR model also broadly apply to the REA ontology. However, the Supply Chain Council (publishers of the SCOR model) clearly state, "SCOR does not attempt to describe every business process or activity." Notably, SCOR does not describe sales and marketing (demand generation), R&D, post-sales service, training, and other activities not directly related to supply chain operations. Thus, the REA model is a better fit for many strategic planning purposes than the SCOR model.

IV. USE OF REA FRAMEWORK TO SUPPORT SIMULATION MODELS

In this section we further describe how the REA framework supports the development of simulation models. In particular, we explain how it supports the abstraction from the real-world domain that is key to simulation modeling process. Then we describe how integration between three REA infrastructure layers describe (1) *what could be*, (2) *what should be*, and (3) *what is* to support learning in the strategic planning process. Prior research (Geerts & McCarthy 1999, 2002; Dunn et al. 2004; Church and Smith 2007) establishes the REA framework as an enterprise domain ontology. The resource-event-agent patterns depict the information architecture related to enterprise economic activity at the accountability level. Corresponding type images model the enterprise policy infrastructure and define the enterprise control structures (Geerts and McCarthy 2002, 2006).

Linking Simulation Models to the REA Policy Infrastructure

Geerts and McCarthy (2006) further differentiate enterprise policy infrastructure from accountability infrastructure. The policy infrastructure defines the economic activities "that should, could, or must happen" within the enterprise (Geerts and McCarthy 2006, 39). The integration between the policy infrastructure and the accountability infrastructure imposes management control by establishing guidelines and constraints on the economic activity and allowing managers to compare actual performance against planned performance. Figure 3 shows an example of the links between the REA policy and accountability infrastructures.

For simulation modeling, we differentiate between policy-level objects that establish what could be, and those that define what should be. To specify what should (or must) be, the policy-level objects reflect constraints or performance targets established by management on the underlying economic activity to accomplish the strategic goals of the organization (Geerts and McCarthy 2006). These policy-level objects establish validation rules, standards, budgets, and business policies. For simulation models, the policy-level objects instead reflect the possible behavioral characteristics of the underlying real-world objects as they relate to the strategic goals for the business process. Managers employ simulation to predict customers' demand behavior with respect to changes in the firms' products value proposition, for example. To specify what could be, managers consider possible alternative constraints, standards, performance targets, and related variability in economic activity.

For example, Figure 4a presents the relationship between a product type object (policy level) and the corresponding product object (accountability level) as shown in Geerts and McCarthy (2006, Figure 11). The product type object includes targets, validation rules,

[4] A broad web search located some discussion of the balanced scorecard as an appropriate strategic planning ontology, but the REA framework also encompasses a balanced scorecard framework (Church and Smith 2007).

FIGURE 3
Integration between Policy Level and Operational Level (Based on Geerts and McCarthy 2006, Figure 1)

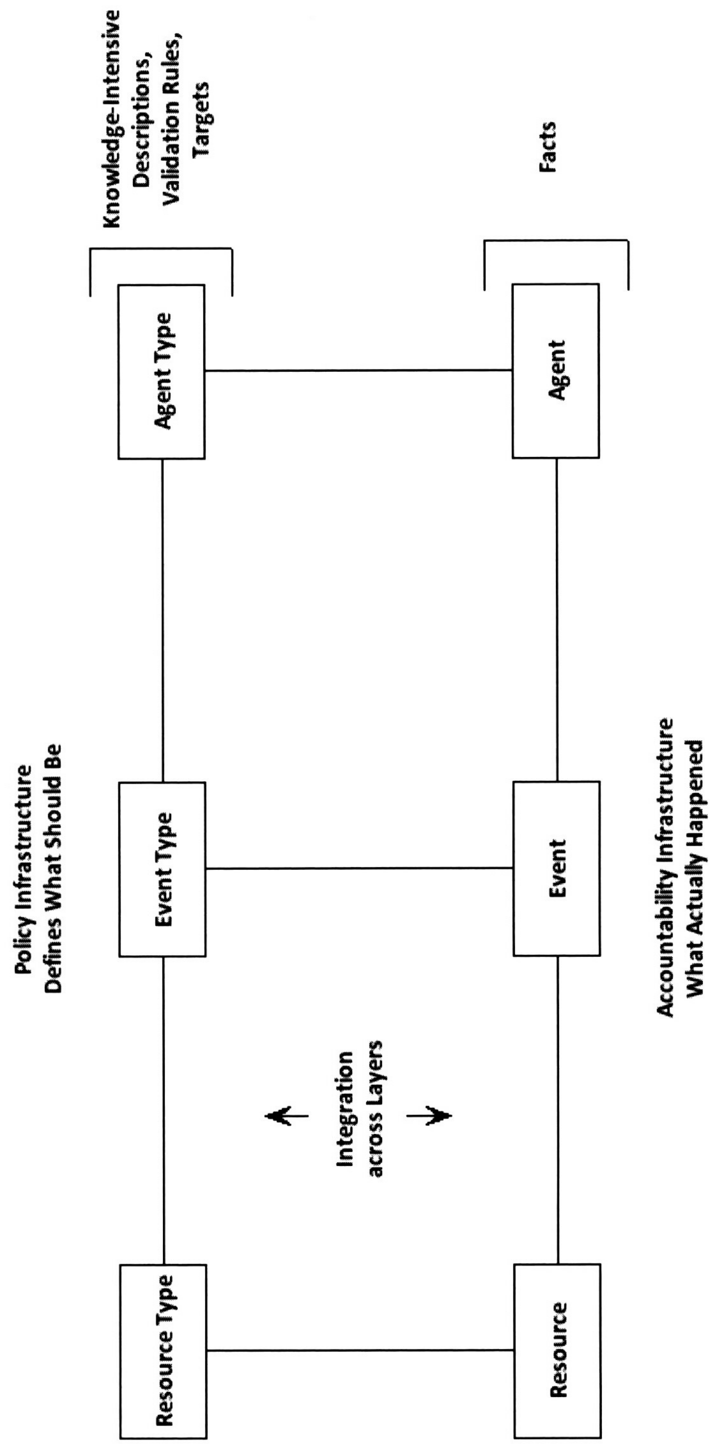


FIGURE 4a
Example of Policy Level and Accountability Level Integration (Based on Geerts and McCarthy 2006, Figure 11)

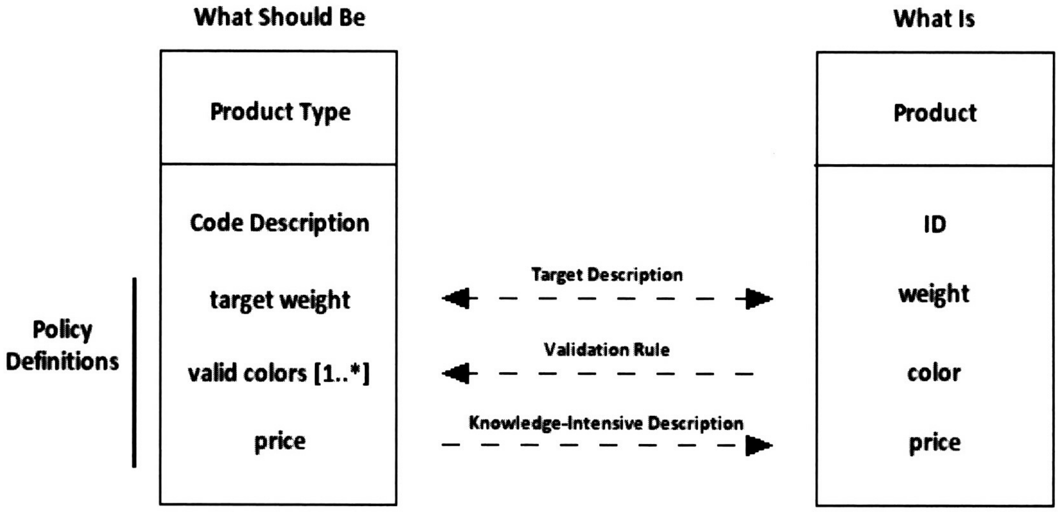
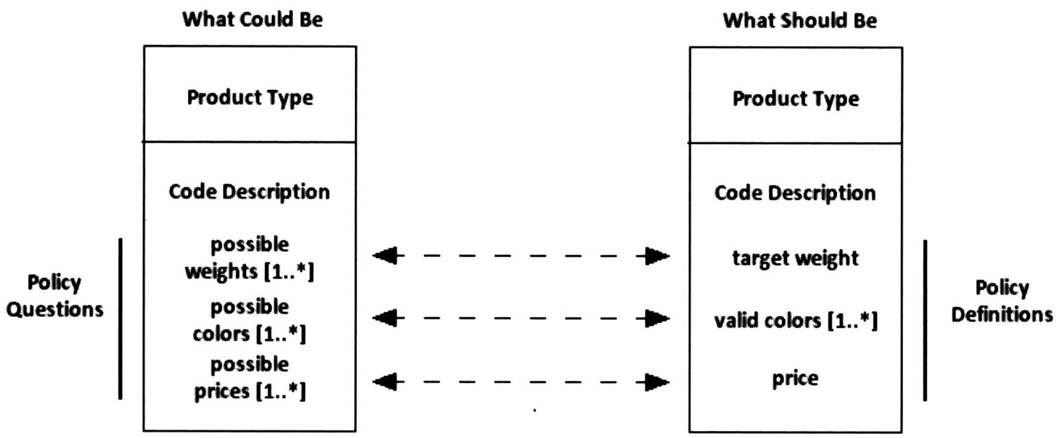


FIGURE 4b
Example of Integration between Policy Level for Simulation and Policy Level for Control



and knowledge-intensive descriptions applicable to the corresponding product (real-world economic resource). Figure 4b then presents the link between policy-level object for control purposes, specifying *what should be*, and the object for simulation purposes, specifying planning questions about *what could be*: what are the possible weights, colors, etc., and how do those affect the range of prices?

Figures 5a and 5b and Table 3 provide additional examples. For simulation, managers are interested in the range of customer characteristics affecting demand, as well as the effect that the firm's value proposition has on customer demand (Kaplan and Norton 2004).

FIGURE 5a
Association between Customer Types and Sales Types

FIGURE 5b
Associations between Resource, Event, and Agent Types with Stratifications

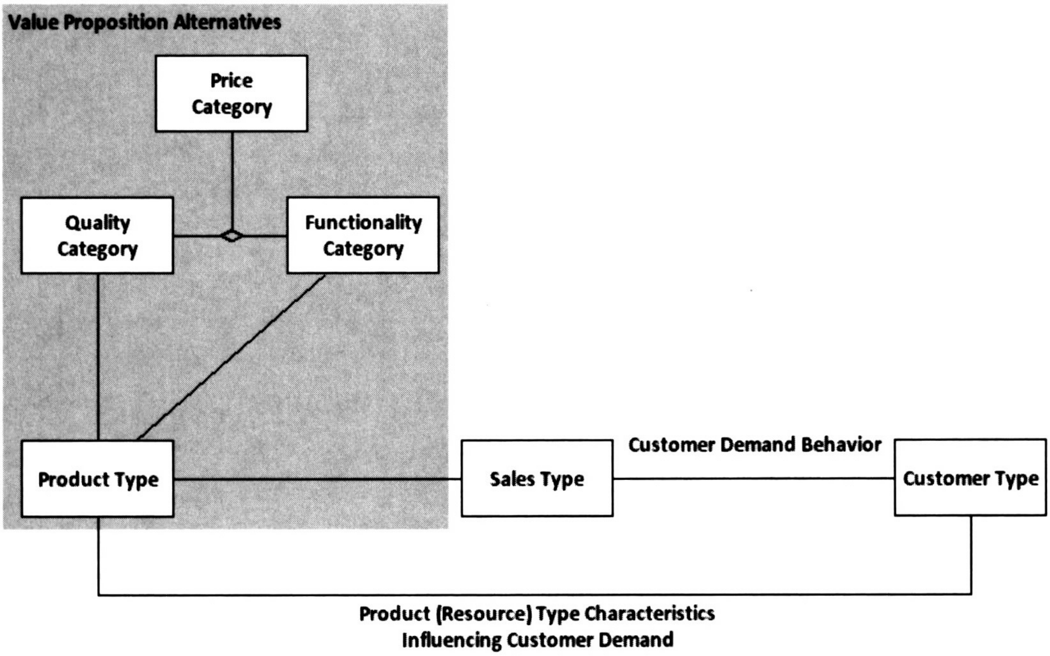


Figure 5a models the relationship between sales types and customer types. Managers would identify the likely characteristics of each customer type that cause desired customer behavior, i.e., participation in corresponding sales types. In other words, what characteristics are expected to influence customers' buying behavior?

Figure 5b provides a more complex example to show how combinations of product attributes related to the expected value proposition might affect customer demand patterns. In this case the characteristics of the product type are linked to various categories of price, quality, and functionality. Price, quality, and functionality are elements of the customer value proposition described in Kaplan and Norton (2004). Thus, the value proposition, indicated by characteristics of the product type, should affect the buying behavior of certain customer types, which would then affect corresponding periodic sales. Using this model, managers could then develop ranges of possible values for the products' price, quality, and functionality characteristics and consider possible corresponding impacts on customer demand.

TABLE 3
Simulation Objects and Sample Questions for Sales/Cash Receipts Process

Simulation Object Types	Examples of Questions for Simulation	Cause (C)/ Effect (E)?
	Questions on subjects listed below relate to distributions of possible values, constraints on those distributions, how those values might be related, and how those values might be affected by strategic initiatives.	
Resource Types[a]		
Inventory	Product features: price, quality, availability, selection, functionality	C1
	Product cost	C1
	Inventory levels and periodic changes in inventory levels	C1
Cash	Cash levels and periodic changes in cash levels	
Event Types[b]		
Sales	Periodic sales rates and cumulative sales over time	E3
Cash receipts	Periodic cash receipts rates and cumulative cash receipts over time	
Agent Types[a]		
Employees	Quantity of employees	
	Event processing capacity per employee	
	Employee skill levels	
	Employee pay levels	
Customers	Quantity of customers	E2/C3
	Customer demand and periodic changes in demand	E2/C3
	Customer satisfaction given product/service attributes	E1/C2

Cause/Effect column shows expected cause and effect relationships consistent with Kaplan and Norton (2004); product attributes determine value proposition which in turn affects customer satisfaction, customer demand, and number of customers, which in turn affects sales rates.

[a] Questions for these object types to be determined primarily by enterprise managers.

[b] Questions for Event object types to be examined with the simulation once managers determine possible alternative for the Resource and Agent object type questions.

Table 3 further describes examples of questions about various policy-level object types for a sample sales process to establish simulation parameters. In general, the questions relate to how specific strategic initiatives, such as investments in information systems, and alternative scenarios affect expected levels or distributions of attribute values and expected associations among object types. First, managers address the elements of future performance under their control. Consistent with Figure 5b, managers would stipulate expected levels of product characteristics, relationships among those characteristics, e.g., price and quality tradeoffs, and the likelihood that the enterprise will consistently achieve those product characteristics in a competitive market. They would then estimate the corresponding effect on customer demand levels based on the likely number of customers, changes in the number of customers, and changes in customers' expected satisfaction with those product characteristics. These estimates certainly require judgment and could be biased, but the overall process of developing these estimates in the context of a business process model with links to current accounting information should reduce that bias. Next, they would run the simulation over a time period of interest to determine likely effect on sales distributions.

Using this process, managers could test the sensitivity of sales to particular combinations of product attributes and customer demand estimates. Finally, they could consider the impact of proposed strategic initiatives on product characteristics, customer factors, sales rates, and overall financial performance, as Kaplan and Norton (2004) generally describe in connection with use of a strategy map.

How the REA Policy and Accountability Infrastructures Support Simulation Modeling

Integration between policy and accountability infrastructures allows managers to compare plans against actual (Geerts and McCarthy 2006). The close correspondence between *what could be* and *what should be* policy-level objects then allows managers to consider relevant future alternatives in simulations based on current plans and past actual performance. Figure 6 links the accountability level to the management control policy level and then to the simulation policy level. Collectively, the links also support (1) the use of current performance data (accountability level) in considering reasonable alternatives for the future, (2) the detailed design of the simulation model, (3) the verification and validation of simulation models, and (4) the analysis of the results of the simulation, because the simulation model and subsequent experiment results are directly tied to prior actual performance for business processes. This tight integration helps reduce the bias in managers' knowledge bases and context representation, since it clearly links operations to abstractions that summarize information for management.

Furthermore, this integration would facilitate (1) collecting business process data to support the simulation, and (2) using the simulation results to adjust the policy-level knowledge-intensive descriptions, validation rules, and target descriptions. Thus, managers could use summary information from past business process performance to set initial values for the simulation resources and the level of process activity. They could then adjust these values to reflect the particular strategic alternatives under consideration. Of course, the managers would be interested in the incremental costs or benefits of each alternative.

This extra infrastructure layer also supports double-loop learning (Kaplan and Norton 1996, 2001; Senge 1990). As shown in Figure 7, the first loop involves integration between the strategy implementation and operational levels. For example, budget levels determine resources allocated to a process to achieve an expected level of results. The actual process results can be compared against the expected levels and managers can then adjust the resource allocations appropriately to enforce policy. This loop is well defined by the accountability and policy infrastructure integration in Geerts and McCarthy (2006, Figure 1).

The second loop shown in Figure 7 involves integration across all three levels: strategy formulation, implementation, and operations. Feedback from operations further evaluates the effectiveness of strategic decisions (e.g., Kaplan and Norton 2001). When significant discrepancies arise, the managers could also reevaluate those strategic alternatives not selected in earlier analysis. Continued failure to achieve expected results based on planned resource allocations could require adjustments to the strategy.

Importantly, tying simulation models for strategy formulation to existing models for strategy implementation and operations allows tests of the strategy formulated from the simulation models. Those models could be updated and expanded over time as the operational results reflect the enterprise's dynamic competitive environment. Thus, an REA ontology-based simulation model could be reused, which should reduce subsequent development costs.

FIGURE 6
Integration from Accountability to Control to Simulation Levels

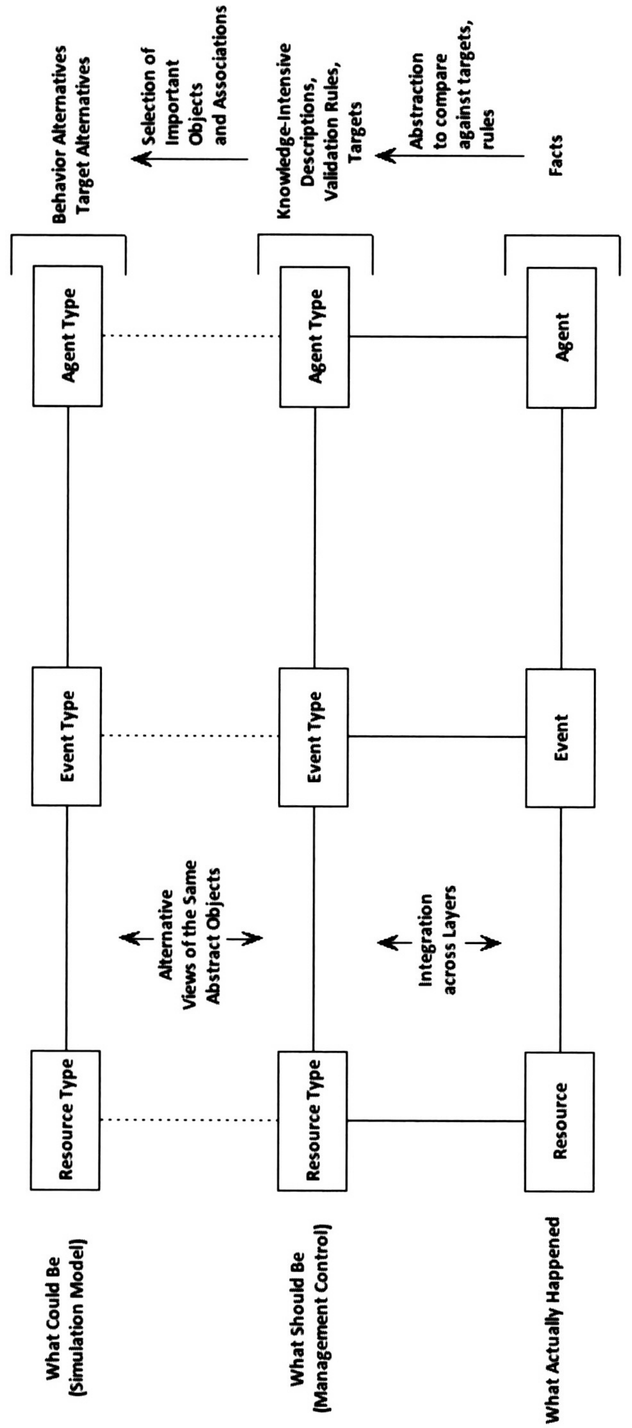
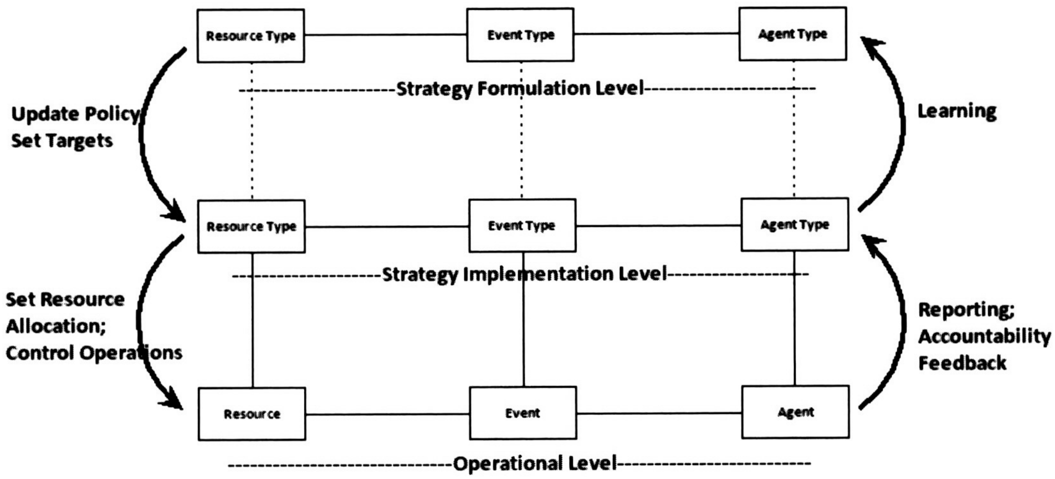


FIGURE 7
Double Loop Integration between Strategy Formulation, Strategy Implementation, and Operation



V. EXAMPLE USING THE REA FRAMEWORK TO DEFINE A SIMULATION MODEL

In this section we develop a simple example applying the REA framework to a simulation model as a proof of concept. An extensive example is beyond the scope of this paper. We also provide an example of how that model might be used to support managerial decision-making. For this example we use systems dynamics techniques, and we employ iThink software from ISEE Systems, Inc. Although there are other similar software products, e.g., Vensim from Ventana Systems, Inc., the iThink product is widely used in system dynamics academic research. We follow the conventions for modeling stocks and flows described in Sterman (2000), Richmond (1997), and iThink and Vensim tutorials. We recognize that this particular approach requires some implementation compromises, just as expected when implementing REA models in any accounting software.[5]

System dynamics, which originated with Jay Forrester's work at MIT in the 1950s, is the study of complex systems through an examination of system stocks, flows, and feedback loops through computer simulation models. System dynamics methods provide "useful insight into situations of dynamic complexity," especially when experimentation with real systems is impractical or infeasible (Sterman 2000, 39). According to Sterman (2000), system dynamics is an interdisciplinary approach to examining complex systems, such as business processes. It uses stock and flow models to simulate the behavior of complex systems over time.

We select systems dynamics techniques for this example, because these techniques have been used for strategic planning applications in prior research (e.g., Winch 1999; Morecroft 1999; Sterman 2000), and it is particularly suited to situations involving higher levels of abstraction, such as strategic analyses of business processes (Greasley 2004; Sterman 2000).

[5] We also make no claim that iThink is the best simulation software for implementing an REA ontology-based planning model.

Greasley (2004) differentiates between static and dynamic simulation techniques. Static techniques include Monte Carlo computational systems. Dynamic simulations can be further subdivided into discrete event simulation and systems dynamics models. Discrete event simulation is typically used in situations where the system variables change at discrete points in time, such as in manufacturing planning or customer service analysis. Systems dynamics is typically used when the system of interest may change continuously over time.

Creating REA-Based Dynamic Models of Business Processes

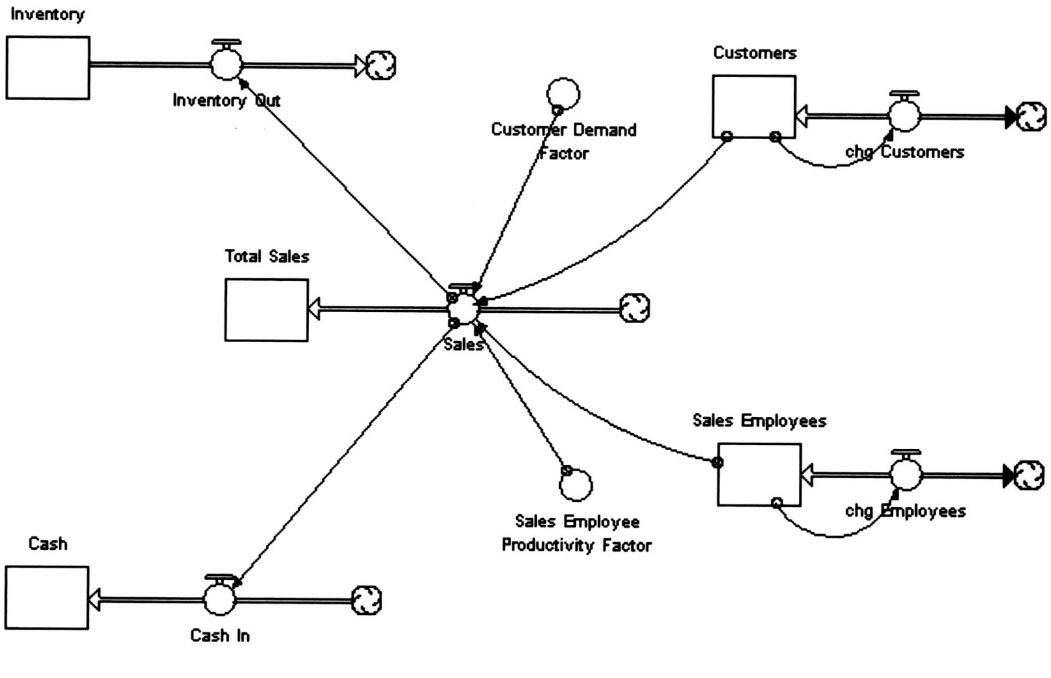
Stocks and flows are the basic building blocks of systems dynamics models. Stocks represent accumulations, such as inventory values, cumulative sales revenue over time, or the number of employees. Flows represent changes in stocks, such as shipments from inventory or receipts into inventory. The relationship between stocks and flows can be described mathematically:

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0) \quad (1)$$

where *Inflow(s)* is the value of the inflow and *Outflow(s)* is the value of the outflow from the stock at any time, s, between the initial time, t_0, and the current time, t.

Using the sales/collection process as an example, we based our simulation model shown in Figure 8 on the policy-level objects in the REA framework as follows:

FIGURE 8
Basic Simulation Model of Sales Process



- REA resource types (inventory and cash types) become stocks, shown as rectangles, which represent the accumulated values over the selected simulation period.
- REA event types (sales and cash receipts types) become stock inflows and outflows, shown as pipes with valves, representing periodic sales and cash receipt amounts. For the planning model, managers are not interested in tracking individual transactions, but rather the rate of sales transactions. Additionally, we include stocks to represent cumulative sales and cash receipt amounts over time, just as an REA model might include policy-level objects to support cumulative sales reporting (McCarthy [1982] referred to this as conclusion materialization).
- REA agent types (customers and sales employees types) become stocks, because for strategic planning managers are interested in the number of customers and employees at any time and the characteristics of those agents that influence their behavior, i.e., corresponding rates of participation in events. In Figure 7, we also include bi-flow pipes supporting both increases and decreases in the number of customers and employees over time to allow for dynamic changes to the agent type values.
- The REA relationship between inventory types and sales types is represented by an outflow from the Inventory stock. The typical REA relationship between cash receipts types and cash types becomes an inflow to the Cash stock. These flows represent the periodic changes in the stocks.

We make implementation compromises due to differences between simulation software and database systems. First, stocks in the simulation can only represent one characteristic of a related REA object, so we use "converters" (the small circles in the diagram) to represent other relevant characteristics of those objects. The converters allow manipulation of particular characteristics of interest. For example, we include the converter titled *Sales Employee Productivity Factor* to allow managers to adjust that characteristic and examine how that affects their ability to handle sales transactions.

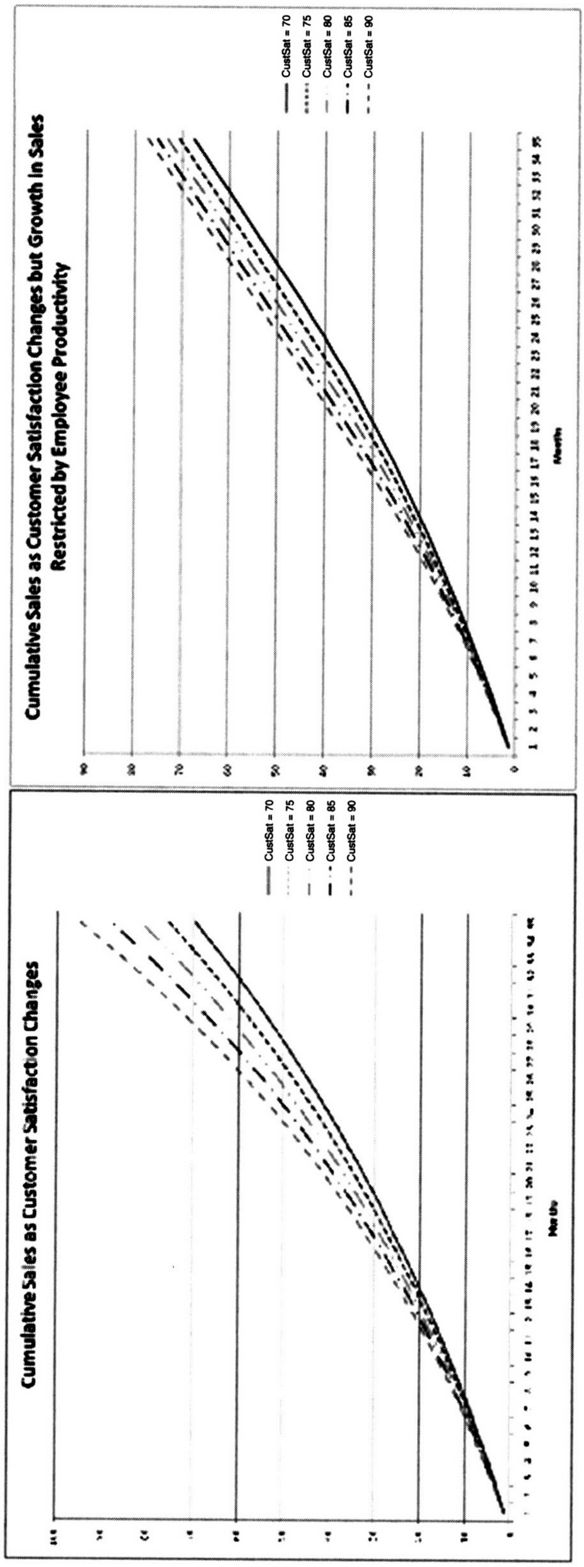
Example Model Operation

Our operational example follows the basic example in Figure 8 except we add a customer satisfaction converter that affects both the customer demand factor (demand per customer) and the number of customers. For this example, we assume that managers are considering the overall impact of a strategic initiative to improve customer management and thereby improve sales growth. The managers are considering implementing a state of the art customer relationship management system that will allow them to improve their relationship with high-value customers, better target their marketing, and increase cross-selling of their products. The firm's senior management expects that increasing customer satisfaction will increase the volume of sales to existing customers and also expand their customer base through positive word of mouth advertising.

For this example, we do not consider the costs of the initiative. We examine only the benefits. We recognize that managers would compare benefits to costs; however, we expect that the costs are relatively easier to determine. The benefits of information systems investments are generally considered harder to quantify (e.g., Bacon 1992). We examine results over 36 months, since Kaplan and Norton (2004) note that most long range planning involves a three- to five-year horizon.

Figure 9 presents results of the simulation showing the sensitivity of sales to customer satisfaction. The chart on the left shows the unconstrained cumulative sales as customer satisfaction increases from 70 percent to 90 percent. The chart on the right shows the cumulative sales constrained by the number and productivity of sales employees. Increases

FIGURE 9
Charts Comparing Simulation Results



to customer satisfaction generate growth in the number of customers, and growth in the number of sales employees is inadequate to keep up. Thus, the potential benefits of the customer relationship management system are limited without a corresponding increase in the number of employees or their productivity levels. This dynamic sales model allows us to simulate the sales process over time and examine the effect of assumptions or policies on future performance. For example, we can change the customer demand or employee productivity assumptions and see the effect on inventory or cash. More importantly, we could expand this model to create an integrated, dynamic model of business processes and tailor the model to specific business situations.

Referring again to Figure 6, we can obtain aggregate information about past performance from the operational (lowest level). We obtain the variables of interest for the simulation from the policy-level objects and their attributes. We then manipulate the attributes by selecting appropriate alternative values at the simulation level that correspond to strategic initiatives under consideration. This coupling ties our simulation model to past results, past levels of management control. It also allows us to readily implement selected alternatives from the simulation by modifying policy-level rules, targets, etc., and thereby track future performance against expected performance.

Summary

In this example, we demonstrate how an REA-based simulation model allows managers to quantify expected relationships and compare alternatives under a variety of relevant conditions. For each set of alternatives, the simulation predicts corresponding performance over time. In a balanced scorecard setting, it forces managers to articulate how various initiatives work to affect firm strategy and where those initiatives may interact to reduce potential benefits. It also formalizes uncertainty by allowing managers to incorporate variance into the model and conduct a variety of sensitivity tests. It therefore supports an informed management discussion of the alternatives. Although simple, the example demonstrates how managers could sequentially introduce options to manage that complexity and foster understanding of the business impacts of strategic initiatives.

Managers could tailor the generic REA ontology-based models to firm-specific situations and then use those models to formalize the expected impact of both qualitative and quantitative factors on business process performance. These models could be readily adapted to new investment decisions and changing circumstances over time, which should reduce the cost of subsequent systems development.

VI. CONCLUDING REMARKS AND RECOMMENDATIONS FOR FURTHER RESEARCH

In this paper we propose an REA ontology-based dynamic enterprise model to facilitate enterprise strategy formulation and implementation. Strategic planning requires managers to predict future performance in a complex and dynamic business environment. To evaluate strategic investments, many enterprises rely heavily on quantitative techniques such as discounted cash flow analysis, which fail to adequately consider uncertainty. Furthermore, they often consider projects in isolation, which fails to adequately consider either cross-functional impacts or project synergies. Consequently, managers make potentially ill-informed resource allocation decisions.

To overcome these problems, enterprises also employ scenario-planning techniques that incorporate management judgment. Scenario planning combines qualitative and quantitative techniques to help address uncertainty and cross-functional issues. Yet, scenario planning requires management judgment and may perpetuate management biases. Modeling and simulation technology can incorporate quantitative analysis augmented by management's qualitative assessments. Modeling and simulation technology helps managers articulate the strategic problem, apply knowledge, and reach consensus. Simulation also provides a low-risk approach to testing alternatives prior to implementation. However, simulation models of complex processes may be complex and costly to develop. We argue that the presence of generic ontology-based dynamic models of business processes would advance the use of a powerful management tool by improving systems development and reducing overall costs.

We also assert that the REA framework—with minor extensions to the policy-level infrastructure—is an appropriate ontology for simulation models. The REA framework provides links between the accountability and policy infrastructure to support the simulation development process. As shown in Figures 4a, 4b, 6, and 7, the existing policy objects support the abstraction necessary to develop the simulation models. The link to operational information, shown in Figures 3, 6, and 7, supports data collection and model validation. Our approach offers generic simulation models based on an established ontology, i.e., the REA framework, which facilitates reuse of and learning from these models in a variety of business contexts.

In summary, we contribute to the design-science literature by extending the existing REA framework to a strategic-planning context and linking the semantics of enterprise planning to those of enterprise operation. We also show how the nature of policy objects for simulation modeling to support strategy formulation differs from corresponding policy objects for management control. Although these are alternate views of the same enterprise policy objects, the simulation model objects address policy questions, i.e., *what could be*, while the management control objects address policy definitions, i.e., *what should be*. The use of the REA ontology facilitates simulation systems development and ties the simulation model closely to existing enterprise policy and operations. Thus, an REA ontology-based simulation model could be reused and expanded as enterprise competitive dynamics change.

We provide only a limited example of an REA ontology-based simulation model. We recommend further research to expand this model into a complete dynamic model of the firm. Such a model could have broad application to a variety of business problems and support academic research into those problems. Although prior research suggests that simulation modeling can reduce cognitive bias, there is little research that confirms that. Thus, we also recommend further research into whether, how, and under what circumstances simulation modeling can reduce cognitive bias and improve strategic decision-making. Gerard (2005) showed that structured domain knowledge reduces conceptual modeling errors. In that same vein, researchers should examine whether structured domain knowledge facilitates simulation modeling in a strategic planning context.

McCarthy's (1982) basic REA pattern has proven robust. It describes the features of business processes necessary to support accounting systems in a database environment. The REA-based dynamic models described herein similarly provide the basic patterns necessary to support a variety of management-planning contexts.

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