BEAM: A framework for business ecosystem analysis and modeling

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This paper presents a framework for the modeling and analysis of business model designs involving a network of interconnected business entities. The framework includes an ecosystem-modeling component, a simulation component, and a service-analysis component, and integrates methods from value network modeling, game theory analysis, and multiagent systems. A role-based paradigm is introduced for characterizing ecosystem entities in order to easily allow for the evolution of the ecosystem and duplicated functionality for entities. We show how the framework can be used to provide insight into value distribution among the entities and evaluation of business model performance under different scenarios. The methods are illustrated using a case study of a retail business-to-business service ecosystem.

INTRODUCTION

As businesses become more and more modularized, characterizing entity relationships and understanding how business decisions or actions taken by one entity impact all of the interrelated entities, both within and among enterprises, becomes a key challenge.[1,2]

Ignoring these interactions can lead to unexpected and potentially undesirable outcomes.[3] Tools that help to systematically characterize the business ecosystem (or network) and analyze the potential impact of different business decisions on each entity in the network are essential for improving business design.

Figure 1 shows a sample ecosystem associated with hosted business-to-business (B2B) transaction services that facilitate supplier-retailer collaborations. In the retail industry, transactions between suppliers and retailers are usually supported by a B2B transaction system that provides order management, settlement, sale reporting, inventory control, and other functions to suppliers. Currently, many such applications are independently built and hosted by retailers. Suppliers have to log on to different systems to conduct transactions with different retailers and pay monthly fees for each system. In an example scenario, an information technology (IT) hosting service provider (Company A) plans to

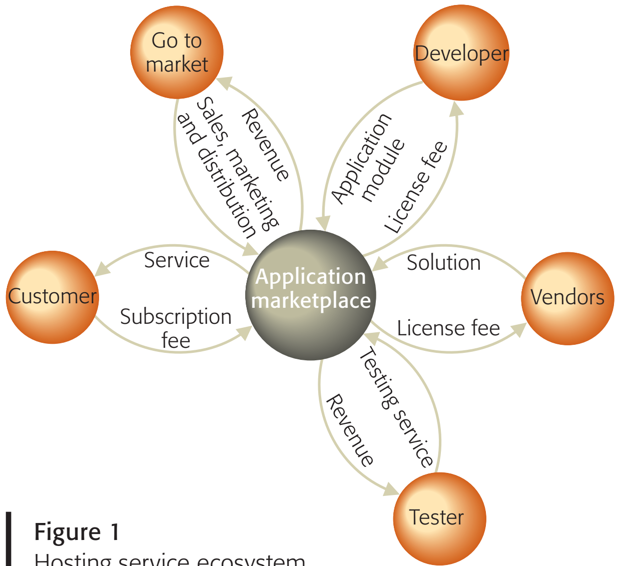

Figure 1
Hosting service ecosystem

develop an integrated hosting B2B portal for the retail industry. For the suppliers, the platform eliminates multiple logins for transactions with different retailers and multiple monthly fees paid to use many different transaction systems. For the retailers, the system reduces maintenance costs of the noncore transaction system. The IT service provider may also benefit if the supplier volume is large. To initiate and grow the service, effective business models are essential. Relevant questions include how to design a revenue-sharing mechanism with retailers, how to design a charging model for diversified suppliers, and how to form an effective business-partner network covering all the relevant business activities, such as application development, platform operation, go-to-market, and delivery.

Typical business-decision-support frameworks assume that the strategic outcome can be defined independently of the reactions of other players. At nearly all levels of the decision process, however, interaction among players is significant. We present a set of modeling and analysis methods within an integrated framework to analyze business-model designs involving a network of interconnected entities. The framework combines ideas from value network analysis[2] for systematic characterization of the ecosystem, game theory[3] for describing fundamental entity behavior, and multiagent systems[4] (MAS) to provide a computational approach for analyzing evolving business models.

While our work is applicable to ecosystems having business offerings of different types, including products and services, we focus our attention here on services ecosystems, which are of special interest in service science research. Related service science research has studied services ecosystems from the viewpoint of interactions within the network, such as social network analysis,[5] swarm intelligence,[6] and network horizon,[7] but has not provided an approach for the systematic analysis of business models for evolving services ecosystems.

LITERATURE REVIEW

In this section, we briefly summarize relevant prior work on value network analysis, game theory, and MAS—the three areas that underlie our proposed business ecosystem analysis and modeling framework.

Value chain and network

A service ecosystem can be considered a value cocreation configuration of people, technology, shared information, and value propositions connecting internal and external service systems.[8] This notion is closely related to the value chain and network concept describing the tangible (such as goods, services, and revenue) and intangible (such as knowledge) transactions between different business entities. In the context of a value chain, Allee[9] describes relationships between business entities by three types of value transactions: goods, services, and revenue; knowledge; and intangible value. We make use of these ideas in developing the characterization of a business ecosystem as presented in this paper.

In value network research, a *business model* is typically used to describe the roles and relationships of a company, its customers, partners, and suppliers, including the flow of goods, information, and money among these parties and the financial benefits for those involved.[10,11] In this paper, we are using the term *business model* in the same way, whereas we use the term *business network* only when referring purely to the ecosystem network structure.

Game theory

In traditional economic analysis, interactions among multiple business partners are often evaluated in the context of a global optimization problem in which demand-supply and cost-price are balanced. In contrast, a game-theoretic approach takes individual preferences and hidden information into consideration, providing additional insights useful for understanding competitive environments. Game theory has been used to analyze the behavior of multiple partners under information asymmetry or a decentralized decision-making environment in supply chains.[12,13] This work provides valuable insights into tactical planning in inventory management, order management, pricing mechanism, buyback strategy, lead time, and product quality assurance.

In this paper, we adopt game-theoretic techniques for the design of business models in a service ecosystem. Previous applications of game theory to the analysis of a network-based services environment include, for example, Baron et al.,[14] who studied the combination of admission control with pricing on customer choice of usage level in an IT hosting service.

Multiagent systems

Classical game theory is based on explicit analytical methods, making it difficult to extend beyond two or three participants. However, computational methods are typically used in the context of MAS, that is, loosely coupled networks of problem-solver entities (agents) that work together to find answers to problems that are beyond the individual capabilities or knowledge of each entity.[15] The term *MAS* is used for all types of systems composed of multiple autonomous components that show the following characteristics:[16]

- Each agent has incomplete capabilities to solve a problem
- There is no global system control
- Data is decentralized
- Computation is asynchronous

Recent research in the area of designing MAS coordination mechanisms and agent-decision-process modeling[17] has adopted game-theoretic approaches for analysis of MAS. We use a similar approach here, providing a game-theoretic approach for business-model design based on computational techniques adopted from MAS. The next section provides the details of our approach.

MODELING AND COMPUTATIONAL TECHNIQUES FOR BUSINESS GAME ANALYSIS

As cited in the previous section, much work exists that is applicable to systematic modeling and analysis of business strategies. However, a number of challenges arise in applying existing technologies to service ecosystems because they tend to be complex, adaptive systems whose configurations and boundaries change over time.[8]

The three main challenges are:

1. *Allowance for evolution of and duplication in roles over the service life cycle*—Company A may initially carry out almost all necessary business activities itself, just as many hosting companies did in the past. As the business grows, however, Company A may decide to provide an online marketplace and hosting platform and collaborate with business partners for other business activities. For example, go-to-market (GTM) partners can market and deliver the applications on the platform while related solutions can be developed by vendors. However, many business activities remain unchanged no matter which entities play the GTM role. A useful business ecosystem-modeling tool needs to take these common elements into account to allow for easy reconfiguration of the network structure as the ecosystem evolves. Later, we introduce a role-based modeling approach in the section "Service ecosystem modeling" to accomplish this task.
2. *Methods for systematic study of interactions among many business entities*—Traditional game theory analysis typically focuses on interactions between two or three parties. The MAS approach allows extension to multiple parties.[17] Here, we provide an integrated approach to combine MAS and game-theoretic techniques within the context of a role-based value network model.
3. *Validation of the ecosystem model and assumptions*—We propose an approach that integrates the collection and assessment of data within the analysis framework to validate and refine the model and assumptions. We also incorporate analysis methods that allow for model uncertainty.

Modeling and analysis components

Based on the analysis requirements outlined above, ***Figure 2*** shows the architecture of our proposed system.

At the foundational level, the service ecosystem modeler provides a way to describe the service ecosystem entities and the relationships among

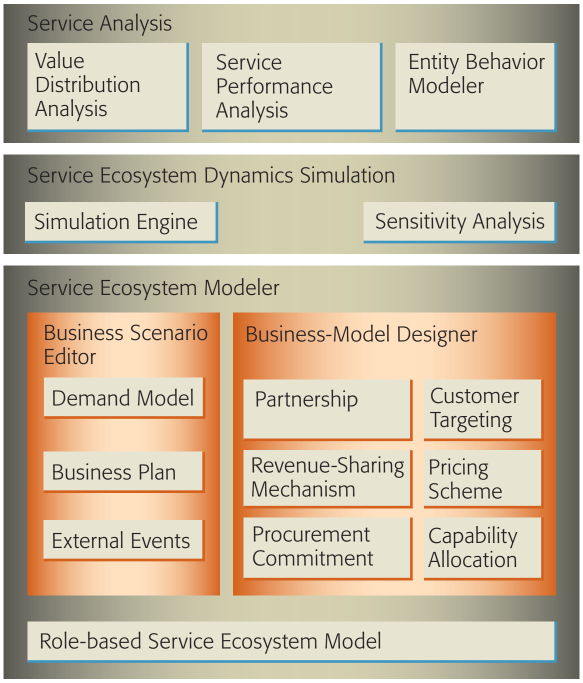

Figure 2
BEAM system architecture

them (that is, the network structure) through the role-based service ecosystem model. The business model designer is a configuration component used to specify attributes of the entities in the network according to their roles. These attributes pertain to elements of the business that are under the control of the business entity; for example, the price charged for a service. In contrast, the business-scenario editor defines scenarios that have an impact on the business and are outside the control of the involved parties; for example, external market events and customer demand.

In the layer that simulates the dynamics of the service ecosystem, the simulation engine module calculates the static and dynamic performance of the service ecosystem, while the sensitivity analysis module evaluates the model results, allowing for uncertainty in model parameters.

At the service analysis layer, the value-distribution analysis module calculates the value of each business entity under the assumed business model based on specified metrics; for example, financial metrics such as revenue and cost. The service performance analysis module provides a more dynamic picture of how the service is provided and consumed, as well as the effectiveness of business models in different business phases. The entity behavior modeler provides the capability to model service demands, customer choices, partner production, and competitors based on real operational data. These results can be used to populate elements of the service ecosystem modeler, as well as provide additional insights into elements of the business design, such as customer targeting, promotion planning, service pricing, and service-capacity planning. Other analysis modules can be added to this layer as needed.

Service ecosystem modeling

In a business service ecosystem, the functions and activities of an entity may overlap with those of other entities and evolve over time. If entities and their relationships are modeled directly, it will be difficult to change them according to an evolving business model over the service life cycle. The model diagram may also become complex, as there may be many duplicate model elements.

We define a *role* as an aggregation of common functions, including activities, decisions, and metrics. In the role-based service ecosystem model, each business entity acts as an independent agent that plays multiple roles according the business-model specification and makes decisions based on its goals, information set, and constraints by sensing environmental changes. In this approach, most of the service ecosystem attributes are specified in the role model. For business entities and their relationships, only information that may differ from one company to another needs to be specified, such as the cost of an IT architect. The basic modeling elements of a role-based service ecosystem business model are shown in ***Table 1***. Additional detail is given in the following sections.

The fundamental mechanism of business game analysis is the linkage between resources, activities, and decisions. A business entity performs activities, needs investment in resources, and has certain performance metrics. The specific business model determines the decision rights allocation and partnership model for a business entity. The decisions impact activity execution, which in turn is quantified by metrics. With such linkages, the cost of activity execution and the impact of decisions on business metrics can be calculated. The business model governs the relationship among agents.

Table 1 Service ecosystem model elements

Class	Concept	Properties
Resource	Such elements as monetary, human capacity, machine, software, and power that can be consumed in the execution of business activities or invested to realize a service	Owner Unit cost
Activity	A task that uses resources	Resource consumption
Decision	The selection of a course of action among variations, such as pricing and capability allocation	Objective Decision variable set Constraint set Related decision variable
Metric	Performance indicator of a business object (activity, business entity, or service ecosystem)	Business object Value
Role	A set of connected activities and decisions in a service ecosystem	Activity list Decision list Metrics list
Business entity	A general term used for enterprises, business units, and regulators	Goals (e.g., payoff function, risk attitudes) Demographic properties (e.g., capacity, size, and location)
Business model	The roles and relationships of a company, its customers, partners, and suppliers, as well as the flow of goods, information, and money among these parties and the financial benefits for those involved	Partnership Decision-making structure Decision-making mechanism

Model elements

Details of some of the model elements are given in the following sections.

Decisions

Decisions directly affect business-activity execution. For example, decisions on capability allocation directly determine how resources are utilized in related business activity execution. According to game theory, a decision D_i comprises four parts: an objective DO_i, a decision variable set DV_i, a constraint set DC_i, and a related decision variable set RDV_i associated with roles that influence the objective of the role of interest. That is, $D_i = (DO_i, DV_i, DC_i, RDV_i)$. The *rational* decision-making process can be expressed as an optimization problem:

$$\max_{DV_i} DO_i(DV_i, RDV_i)$$

subject to

$$DC_i \leq \mathbf{0}.$$

The value proposition evaluation of the consumer can be modeled as a customer decision. The decision result will impact the volume of service consumption (an *activity* in the metamodel) which, in turn, has an impact on the revenue (*metrics* in the metamodel).

Roles

A role is a set of connected activities and decisions within the service ecosystem. Each role is described by the following three properties: a *metrics list* used to measure the performance of the role, a *decision list* that lists all the decisions the role can make, and an *activity list* that lists all the business activities played by the role, where activities, metrics, and decisions are each elements of the ecosystem model. Role k is given as

$$R_k = (\{A_i : r(A_i) = R_k\}, \{D_i : r(D_i) = R_k\}, \{M_i : r(M_i) = R_k\}).$$

Here, $r(A_i)$, $r(D_i)$, and $r(M_i)$ denote the role associated with activity A_i, decision D_i, and metrics M_i, respectively.

The metrics can follow a hierarchal structure. Some metrics can also be directly linked to a business activity or process or to decision variables. For example, the metric *service revenue* is closely related to the pricing-scheme decision process. The value of a metric is a function of decision variables and lower-level metrics or metrics from other roles that influence the current role.

Role relationships

In value network research (e.g., Allee[9]), role relationships are usually categorized into two types: transfer links and influence links. *Transfer link* describes the flow of products, services, monetary instruments, or information between roles. *Influence link* describes the interactions in decision making and the impacts on metrics, which can happen between roles as well as between the entities in the same role. An example of an interaction in decision making is that the pricing scheme of a service provider causes changes to the volume of procurement and usage on the part of its service consumers. An example of metrics influence is that the sales volume of GTM has a direct impact on the revenue of the platform operator.

There are two types of influence links between decisions. The first is a directed linkage from decision D_i to D_j $(i \neq j)$, which, in the language of game theory, represents a Stackelberg game[12] with D_i as the leader and D_j as the follower. The second influence link is an undirected linkage between decision D_i to D_j which represents a Nash game.

As the set of decision points grows, the set of possible combinations of decision interactions can become complex. For example, there are eight possible combinations of the two decision linkage types described. To reduce complexity, we only allow the following two possibilities in the second-level combination: in a Stackelberg game, only the follower decision is a Nash game; in a Nash game, each or one of the decision points is a Nash game. Thus, even with further combinations, only three types of game structures are possible: a pure Nash game with two or more players, a pure Stackelberg game (one leader, one follower), and a Stackelberg game with Nash game embedded in the follower part (one leader, multiple followers).

Business entities

In designing entity relationships, in addition to attributes based on the role of an entity we allow entity-specific attributes and relationships. Entity relationships may need to be considered in the context of certain decisions. For example, two entities may be in a win-win relationship with regard to one service, but may be competing with each other in another service area. In decision making, the competition in other areas should be considered.

Business model

The business model specifies characteristics of the network from three perspectives:

1. Specification of how roles are played by the entities. We use a partnership model where $P_{ij} \in [0, 1]$ denotes the percentage of the role R_i played by entity E_j, $P \in R^{M \times N}$ with $\sum_{j=1}^{N} P_{ij} = 1$.
2. Specification of the decision-making structure, including the following:
   - Decision rights allocation. For example, in service sales, decision rights allocation determines who will decide the service pricing scheme: the platform operator or the GTM entity
   - How often the decision can be revised
3. Specification of specific business strategies including the following:
   - Demand-side policies, such as customer targeting, pricing scheme, and service bundling
   - Supply-side decisions, such as revenue-sharing mechanisms
   - Internal process-related decisions such as capacity-allocation methods that impact service performance (examples of capacity are human capital and computational resources)

Figure 3 shows a high-level metamodel of the service ecosystem elements and indicates the relationships among the aforementioned model elements.

MAS simulation analysis of service ecosystem dynamics

We use simulation to analyze the service ecosystem dynamics after the ecosystem model has been specified. The business activity and performance simulation will switch to decision-making mode if at least one of following conditions is satisfied:

- The business model changes
- The decision update time specified in the business model is achieved
- The trigger condition specified in the decision models is met
- A related decision is updated from other agents

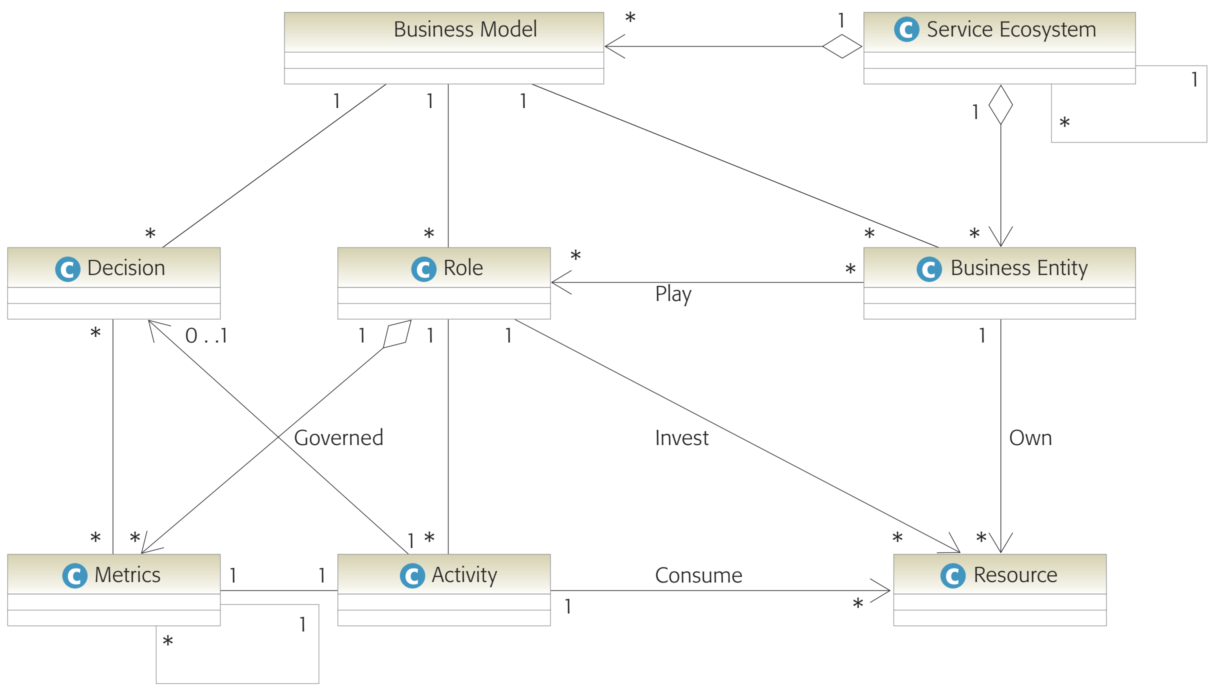

Figure 3
Service ecosystem metamodel

The simulation switches to performance mode when ecosystem equilibrium is obtained. However, before simulation can be conducted, the role-based ecosystem model must be translated into an MAS model. To achieve this, the business model setting and demand model are translated into the environment setting of the MAS model. The business scenarios (for example, external events and decision updates) are generated as system events of the MAS system. Each business entity corresponds to an agent. The transformation from entity-based analysis to role-based analysis is accomplished as follows:

1. Attribute generation: The decision, metrics, and activity list of an entity is the aggregate of the decisions and metrics of the roles that the entity plays. That is, the decision and metrics list of a business entity inherited from the role model are expressed as

$$E_k = (\{D_i : r(D_i) = R_m \text{ and } P_{mk} \neq 0\}, \{M_i : r(D_i) = R_m \text{ and } P_{mk} \neq 0\}).$$

2. Decision interaction generation:
   - *Split*—The linkages between entity decisions are automatically generated according to the relationships in the corresponding role model. That is, if there is a linkage between D_i and D_j in the role model, the same linkage will be assumed between the instances of these decisions in the different entities. An undirected linkage (that is, a Nash game) will be specified for instances corresponding to the same decisions.
   - *Merge*—One business entity may play multiple roles. The decision interaction between two decisions D_i to D_j within the same entity E_k is merged as a new decision D^{new}. That is,

$$\max_{DV_i, DV_j} P_{r(D_i),k} \cdot DO_i(DV_i, DV_j) + P_{r(D_j),k} \cdot DO_j(DV_j, DV_i)$$

subject to

$DC_i \leq \mathbf{0}$ and

$DC_j \leq \mathbf{0}$.

If there is a directed linkage from D_i to D_j in a to-be-merged decision D^{new}, then for each D_k that has an undirected linkage with D_j, a directed linkage from D^{new} to D_k will be generated.

For each D_k that has a directed linkage to D_j, an undirected linkage from D^{new} to D_k will be generated. If there is the undirected linkage from D_i to D_j in a to-

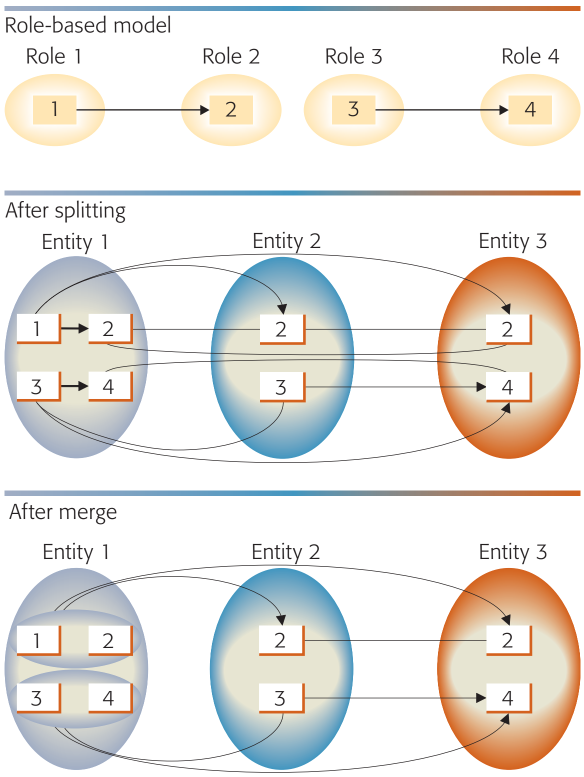

Figure 4
Decision interaction transformation

be-merged decision D^{new}, the linkage will be retained between D_k and D^{new}, where D_k denotes the previous decision that had the linkage (directed or undirected) with D_i or D_j. A simple example is shown in ***Figure 4*** to illustrate the process.

According to the assumptions on game structure above, the possible game structures in this entity model are:

- A pure Nash game
- A pure Stackelberg game (one leader, one follower)
- A Stackelberg game (one leader) with a Nash game embedded in the follower part (multiple followers)
- A Stackelberg game with multiple leaders
- A Stackelberg game with multiple leaders with a Nash game embedded in the follower part (multiple followers)

Since the number of layers in these Stackelberg games is no more than two, the game computation can be transformed to an optimization problem. More complex scenarios can be addressed using computational game theory research.[18]

Service analysis

Different types of service analysis can be performed for a specified business model at a specific point in time. For instance, the calculation procedure to obtain value metrics (such as revenue, costs, and cash flow) for each entity is shown in ***Figure 5***.

CASE STUDY

In this section, we analyze the retail B2B service ecosystem introduced at the beginning of this paper. We focus our analysis solely on the perspective of

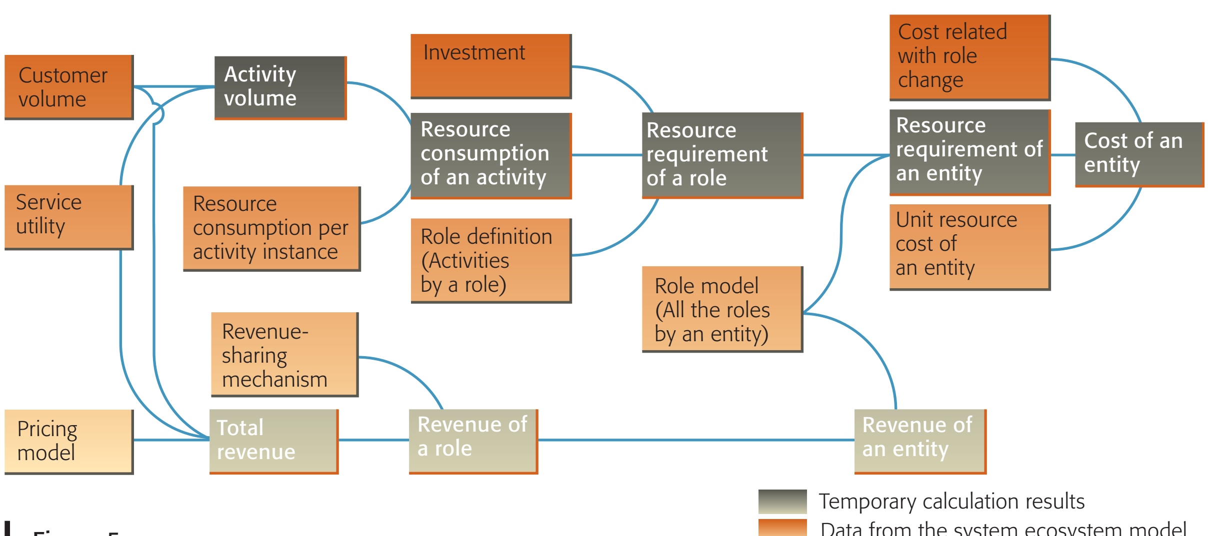

Figure 5
Value distribution calculation

Table 2 Role model of retail B2B service ecosystem

Category	Role	High-level Activity	Potential Player (Business Entity)	Decision
Service consumer		Service subscription Service usage Payment Call for support	Supplier and retailer	Subscribe decision (subscribe or not, module subscribed to) Pricing scheme selection
Service provider	GTM	Service marketing Service sales and contracting	Company A Business partner Retailer	Join or not? Customer targeting Marketing effort and staff allocation Pricing scheme
	Delivery	Application configuration Application implementation Application upgrade	Company A Business partner	Join or not? Configurability Staff allocation
	Support	Call center environment setup Online support On-site support	Company A Business partner	Join or not? Support service level Support resource allocation
	Platform operator	Platform hardware and software implementation System operation and maintenance System upgrade	Company A Business partner (especially telecom platform operator)	Partnership Pricing scheme Revenue sharing Content quality control Computation capacity allocation
	Content provider	Solution development Solution bug fixing	Company A Independent software vendors	Join or not? Content quality Development staff allocation
Competitor		All the activities in the service provider category	Retailers' existing B2B application B2B platform developed by others who come later	All the decisions in the service provider category

Company A, the solution provider, but similar technology may also be applied to analyze other business entities.

Service ecosystem modeling

The roles and potential players and their decisions for this ecosystem are listed in *Table 2*.

The potential interactions between the decision makers are shown in *Figure 6*. Even in this simple case, interactions between decision makers quickly become complicated.

In the next section, we study how environmental factors influence business model selection by using a game-theoretic approach within the context of our proposed framework.

Pricing-decision rights allocation

We consider three decision variables important in a GTM strategy: service price to consumer p, internal revenue sharing rate β, and sale volume Q, and investigate the impact of pricing-decision rights allocation on these decision variables under different scenarios. Assume that the assignment of pricing rights is cost free.

The revenue of the platform operator R_P can be denoted by

$$R_P = (1 - \beta)p \cdot Q.$$

Denoting unit marketing cost as c, the revenue of the GTM party R_G is given as

$$R_G = (\beta \cdot p - c)Q.$$

The willingness of consumers to subscribe usually

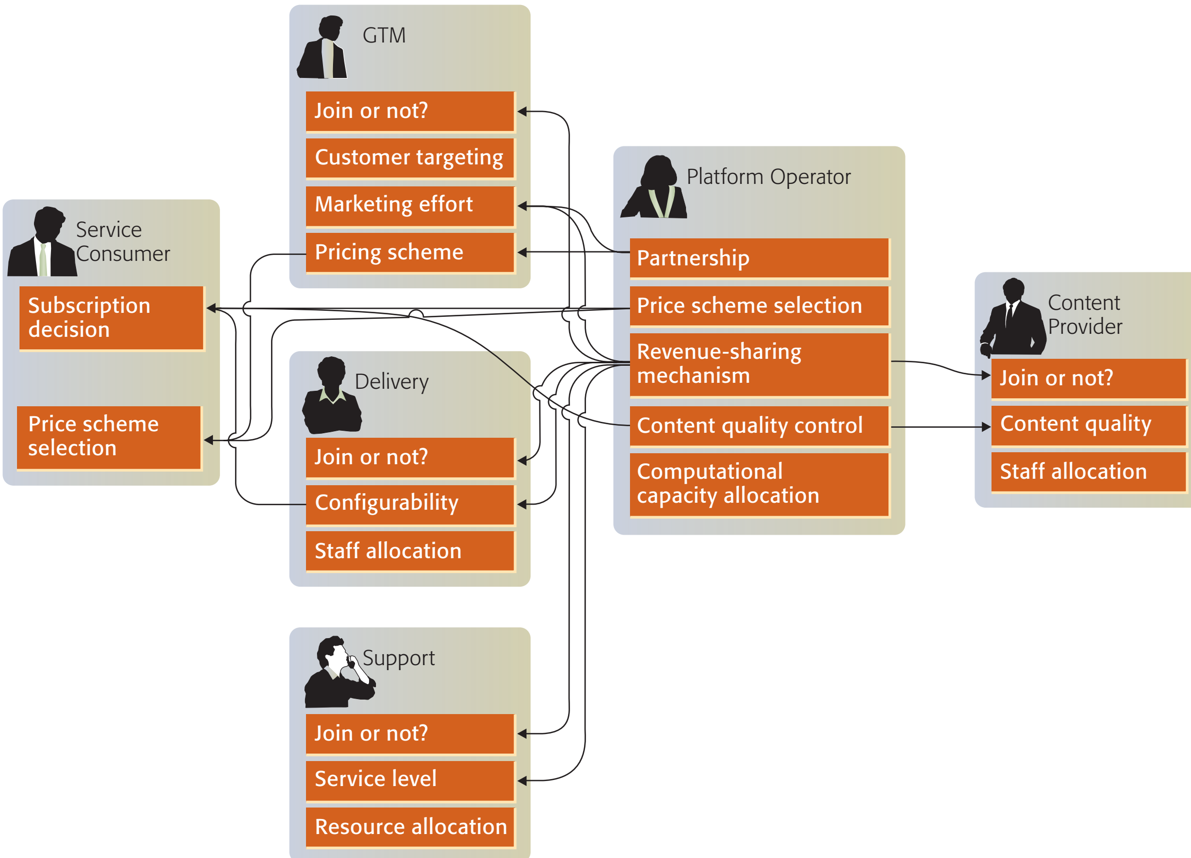

Figure 6
Interactions between decision makers

decreases with p, and unit marketing cost is closely related to the ratio of sale volume Q to real demand. Here assume that the unit marketing cost c is given as

$$c(p, Q) = a \cdot \frac{Q}{D^o - b^o p} = \frac{Q}{D - bp}.$$

Here, D^o denotes the extreme subscription volume when the service is free, b^o is the consumer price elasticity coefficient, and a is the cost parameter. Here, $D = D^o/a$, $b = b^o/a$.

We first consider the scenario in which service consumers are homogeneous and we then compare that scenario to one in which there are two types of service consumers. The third scenario examines interactions among the entities of the GTM roles.

Homogeneous consumer scenario

Ideal case (centralized decision making)—If all the decisions are made by one entity, the optimal decisions are found to be

$$p^1 = \frac{2}{3b} D, \; Q^1 = \frac{1}{9b} D^2.$$

The total revenue is

$$R^1 = \frac{D^3}{27b^2}.$$

Case 1 (pricing right allocated to platform operator)—This case follows a Stackelberg game, that is

$$\max_{p \cdot \beta} (1 - \beta) p \cdot Q^*$$

subject to

$$Q^* = \arg \max_{Q} \left(\beta \cdot p - \frac{Q}{D - bp} \right) Q.$$

The equilibrium decisions under this case are

$$p^P = \frac{2}{3b} D, \; Q^P = \frac{1}{18b} D^2, \; \beta^P = 1/2.$$

The revenues of the platform operator R_P^P and GTM entity R_G^P, are given as

$$R_{\mathrm{P}}^{\mathrm{P}} = \frac{D^3}{54b^2},\ R_{\mathrm{G}}^{\mathrm{P}} = \frac{D^3}{108b^2}.$$

Case 2 (pricing right allocated to GTM)—For this case, the GTM entity is responsible for the service pricing. Thus the optimization problem is changed to

$$\max_{\beta}(1-\beta)p^* \cdot Q^*$$

subject to

$$(p^*, Q^*) = \arg\max_{p,Q}\left(\beta \cdot p - \frac{Q}{D-bp}\right)Q.$$

It can be shown that the equilibrium decisions under this case are the same as for Case 1.

The comparison between the two different decision structures and the ideal centralized case shows:

- Double marginalization[19] from the decentralized decision making causes the inefficiency of the service ecosystem
- When consumers are homogeneous, allocation of pricing rights to the platform operation or GTM gives equivalent results

Heterogeneous consumer scenario

For simplification, assume there are two types of consumers. Group 0 is an insensitive group with price sensitivity coefficient as $b_0 = (1-\gamma)b$ ($\gamma \in [0, 0.5]$); Group 1 is more sensitive, with price sensitivity coefficient as $b_1 = (1+\gamma)b$. However, the price sensitivity heterogeneity is invisible to the platform operator.

Assume the size of consumers under this scenario is the same as that for the homogeneous scenario and the size of these two groups is equal when the service is free. That is, the marketing cost for the two groups is given as

$$c_1(p,Q) = \frac{2Q}{D-b_i p} \quad (i=0,1).$$

Case 1 (pricing right allocated to platform operator)—Because the platform operator has information only on the average sensitivity coefficient b, the problem can be expressed as

$$\max_{p,\beta}(1-\beta)p \cdot (Q_1^* + Q_2^*)$$

subject to

$$Q_i^* = \arg\max_{Q_i}\left(\beta \cdot p - \frac{2Q_i}{D-b_i p}\right)Q_i \quad (i=0,1).$$

The equilibrium decisions for this case are

$$p^{\mathrm{P}} = \frac{2}{3b}D,\ \beta^{\mathrm{P}} = 1/2,$$
$$Q_0^{\mathrm{P}} = \frac{1+2\gamma}{36b}D^2,\ Q_1^{\mathrm{P}} = \frac{1-2\gamma}{36b}D^2.$$

The revenues of the platform operator and GTM are given as

$$R_{\mathrm{P}}^{\mathrm{P}} = \frac{D^3}{54b^2},\ R_{\mathrm{G}}^{\mathrm{P}} = \frac{D^3}{108b^2}.$$

Case 2 (pricing right allocated to GTM)—In this case, the GTM entity can give differentiated prices to different consumer groups. Let

$$\max_{\beta}\sum_{i=1}^{2}(1-\beta)p_i^* \cdot Q_i^*$$

subject to

$$(p_i^*, Q_i^*) = \arg\max_{p_i,Q_i}\left(\beta \cdot p_i - \frac{2Q_i}{D-b_i p_i}\right)Q_i \quad (i=0,1).$$

The equilibrium results for this case are

$$\beta^{\mathrm{G}} = 1/2,\ \ p_i^{\mathrm{G}} = \frac{2}{3b_i}D,\ Q_i^{\mathrm{G}} = \frac{1}{36b_i}D^2 \quad (i=0,1).$$

The revenues of the platform operator and GTM are given as

$$R_{\mathrm{P}}^{\mathrm{G}} = \frac{1+\gamma^2}{(1-\gamma^2)^2}\cdot\frac{D^3}{54b^2},\ R_{\mathrm{G}}^{\mathrm{G}} = \frac{1+\gamma^2}{(1-\gamma^2)^2}\cdot\frac{D^3}{108b^2}.$$

This scenario shows that under information asymmetry and customer heterogeneity, the pricing-decision right should be given to the role that has the customer information.

Heterogeneous consumer scenario with multiple GTM entities

Based on the previous scenario, we assume there are two identical business entities taking a GTM role. Denote $p_i^k (i,k \in \{0,1\})$ as the pricing to customer group i by GTM entity k. Denote $Q_i^k (i,k \in \{0,1\})$ as the sale volume to customer group i by GTM entity k. The marketing cost to customer group i by GTM entity k, c_i^k, can be given as

$$c_i^k(p_i^k, Q_i^k; p_i^{1-k}, Q_i^{1-k}) = \frac{2\sum_{m=0}^{1} Q_i^m}{D - \frac{b_i}{2}\sum_{m=0}^{1} p_i^m} \quad (i,k \in \{0,1\}).$$

Case 1 (pricing right allocated to platform operator)—The game form can be given as

$$\max_{p,\beta}(1-\beta)p\cdot\sum_{i,k=0,1}Q_i^{k*}$$

subject to

$$\begin{aligned}
Q_i^{0*} &= \arg\max_{Q_i^0}\left(\beta\cdot p-\frac{2Q_i^0+2Q_i^{1*}}{D-b_ip}\right)Q_i^0\\
Q_i^{1*} &= \arg\max_{Q_i^1}\left(\beta\cdot p-\frac{2Q_i^{0*}+2Q_i^1}{D-b_ip}\right)Q_i^1
\end{aligned}\qquad (i=0,1),$$

where—in addition to a Stackelberg game between roles (that is, the platform operator and GTM)—there is also a Nash game between the entities of the GTM role.

The equilibrium decisions of this case are

$$p^{\mathrm{P}}=\frac{2}{3b}D,\ \beta^{\mathrm{P}}=1/2,$$

$$Q_0^{m(\mathrm{G})}=\frac{1+2\gamma}{54b}D^2,\ Q_1^{m(\mathrm{G})}=\frac{1-2\gamma}{54b}D^2\quad(m=0,1).$$

The revenues of the platform operator and GTM are given as

$$R_{\mathrm{P}}^{\mathrm{P}}=\frac{2D^3}{81b^2},\ R_{\mathrm{G1}}^{\mathrm{P}}=R_{\mathrm{G2}}^{\mathrm{P}}=\frac{D^3}{243b^2}.$$

Case 2 (pricing right allocated to GTM)—In this case, GTM can give different prices to different consumer groups:

$$\max_{\beta}\sum_{i=1}^{2}(1-\beta)\sum_{i,k=0,1}p_i^{k*}Q_i^{k*}$$

subject to

$$\begin{aligned}
(p_i^{0*},Q_i^{0*}) &= \arg\max_{p_i^0,Q_i^0}\left(\beta\cdot p_i^0-\frac{2Q_i^0+2Q_i^{1*}}{D-\frac{b_i}{2}(p_i^0+p_i^{1*})}\right)Q_i^0\\
(p_i^{1*},Q_i^{1*}) &= \arg\max_{p_i^1,Q_i^1}\left(\beta\cdot p_i^1-\frac{2Q_i^{0*}+2Q_i^1}{D-\frac{b_i}{2}(p_i^{0*}+p_i^1)}\right)Q_i^1
\end{aligned}$$

$$(i=0,1).$$

The equilibrium of this case is

$$\beta^{\mathrm{G}}=1/2,\ p_i^{m(\mathrm{G})}=\frac{3}{4b_i}D,\ Q_i^{m(\mathrm{G})}=\frac{1}{64b_i}D^2\qquad(i,m=0,1).$$

The revenues of the platform operator and GTM are given as

$$R_{\mathrm{P}}^{\mathrm{G}}=\frac{1+\gamma^2}{(1-\gamma^2)^2}\cdot\frac{3D^3}{128b^2},$$

$$R_{\mathrm{G1}}^{\mathrm{G}}=R_{\mathrm{G2}}^{\mathrm{G}}=\frac{1+\gamma^2}{(1-\gamma^2)^2}\cdot\frac{D^3}{256b^2}.$$

When $\gamma<0.02$, the performance of case 1 is better than that of case 2. This means that when there are multiple GTM players and consumers are not so heterogeneous, it is better for the platform operator to do the service pricing. When $\gamma>0.02$, the conclusion is the same as shown in the heterogeneous consumer scenario above.

Compared with the heterogeneous consumer scenario, the existence of multiple GTM entities implies that service pricing and sales volume are a little higher than for single GTM entities because each GTM entity acts independently in decision making. The platform operator benefits more from this scenario, while the payoff for the GTM role declines. This comparison of three simple scenarios shows that the performance of decision rights allocation is sensitive to environmental factors. Although results for these simple scenarios could be worked out analytically, simulation technology is needed to evaluate results for more complex scenarios encountered in practice.

SUMMARY AND DIRECTIONS FOR FUTURE RESEARCH

An important part of modeling and analysis of a service ecosystem is to capture the dynamic interactions among ecosystem business entities. This paper presents a comprehensive framework to integrate business ecosystem modeling and analysis capabilities using MAS as the computation framework, game theory as the fundamental entity behavior model, and value network modeling as a systematic modeling method. A case study of a retail B2B service platform demonstrated how actual system performance can differ from intuition, which does not take into account the effects of interactions among business entities. The techniques presented here are not limited to service ecosystem analysis, but may also be applied in other business ecosystems, such as supply chain analysis.

A few limitations remain in the proposed approach. At a modeling level, certain factors that distinguish services from products are not fully considered. For example, the "simultaneity of production and consumption"[20] for a service and its potential impact on the service dynamics is not investigated. In the simulation, the decision-making interaction across hierarchical levels of a service ecosystem should also be considered. For example, what effect does the decision of an enterprise have on the decision making of a department within the enterprise? At the analysis level, more work is required to develop a holistic approach that can easily allow for different perspectives and different life-cycle stages of the model elements, as well as allow for a larger number of decision-interaction combinations.

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Accepted for publication July 10, 2007.
Published online February 2, 2008 .

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