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Describing coevolution of business and IS alignment via agent-based modeling

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Completed Research

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Abstract

The coevolution of business and IS alignment is a growing concern for researchers and practitioners alike. Extant literature on describing and modeling the coevolution is still in infancy, which makes it hard to capture the complexity and to offer reasonable decisions in the evolution of organizations. This paper focuses on the actors' behaviors, and explores their emergent effects on the holistic alignment. We build an agent-based model to describe the complex alignment landscape and to improve the coevolution governance. The model embraces the emergent behaviors shaped by the interactions of business and IS agents, and guides the coevolution of alignment driven by the external changes. The development of this model forms a necessary step towards suggesting guidance how to analyze and implement coevolution in companies. The paper also shows the capability of an agent-based model to capture some of the emergent behaviors that emerge from bottom-level behaviors.

Keywords

Coevolution, Business and IS Alignment, Complexity, Agent-Based Modeling.

Introduction

Reviewing the research history of business-IS alignment, two distinct conceptualizations are situated in different complexity regions. The first is located in the region of order (Tanriverdi & Lim, 2017), where the alignment exhibits high degrees of stability. A great deal of research has been conducted to establish such an alignment from multiple categories (Henderson & Venkatraman, 1993; Sabherwal et al., 2001; Gerow et al., 2015), levels (Avison et al., 2004; Wagner & Weitzel, 2012), and dimensions (Chan & Reich, 2007; Schlosser et al., 2012). Although differentiating static and dynamic alignment in this region, they all view alignment as a balanced (Sabherwal et al., 2001), cause-effect deterministic logic (Benbya & McKelvey, 2006). The second conceptualization is situated in the region of emergent complexity, where presents high diversity, adaptiveness, connectedness, and mutual dependency (Page, 2009). The alignment in this region moves away from equilibrium and exhibits features like emergence, non-linearity, self-organization, and coevolution (Tanriverdi & Lim, 2017).

The second conceptualization of alignment, which binds a higher level of complexity, goes beyond traditional alignment assumptions and challenges prior methods and models. The coevolutionary theory is deemed as a superior way to address the research challenges (Peppard & Breu, 2003; Benbya & McKelvey, 2006; Tanriverdi et al., 2010). This theory expresses alignment as a coevolutionary process that reconciles top-down rational control and bottom-up emergent adaptation (Benbya & McKelvey, 2006). Beyond the intended planning of alignment, the coevolution aims to coordinate business and IS through continuous adaptation and learning (Peppard & Campbell, 2014). Through near two decades' research on business and IS coevolution, literature has frequently studied the coevolutionary phenomenon (Tanriverdi et al., 2010; Simpson et al., 2016) and the coevolutionary implication(Benbya & McKelvey, 2006; Peppard & Campbell, 2014). Coevolutionary principles (e.g., mutual-communication (Baker & Singh, 2015), knowledge sharing (Simpson et al., 2016), and modular design (Nassim & Robert, 2010)) are sometimes introduced to control the alignment trajectories.

Our previous research has classified the extant coevolutionary literature on alignment from dimensions including focus, framework (Conceptual, Theoretical, Practical), level (Strategic, Operational, Individual), method (Non-Empirical, Qualitative, Quantitative), and phase (Sensing, Sensemaking, Improving, Implementing) (Zhang et al., 2019). As a result, the extant coevolutionary research is still hard to describe the nature of coevolution. Additionally, ten coevolutionary principles were gathered and combined in a systems dynamic model (Zhang et al., 2019). Noteworthy, the computational analysis of coevolutionary alignment is constructive, especially in the region of emergent complexity. As Hedström and Ylikoski (2010) claimed, given the limitations of experimental methods and the complexity of social phenomena, computational analysis is important for this kind of endeavor, which allows systematic exploration of the consequences of modeling assumptions and makes it possible to model much more complex phenomena than was possible earlier. ABM (Agent-Based Modeling) is a microscale model that simulates the operations and interactions of multiple agents to create and predict the appearance of complex phenomena (Allen & Varga, 2006). As a bottom-up modeling method, ABM describes behaviors on the individual level, and predicts organizational behaviors as a cumulative outcome of individual behaviors (Nan & Tanriverdi, 2017). Therefore, ABM is beneficial to capture the emergent complexity of the alignment.

This paper aims to describe the complexity of organizational alignment and to predict the coevolutionary trajectories through an ABM of a hierarchical organizational structure. Our study describes the coevolutionary landscape by modeling how individual-level actions can induce holistic effects in the firm-level strategy with bottom-up paths; how firm-level actions can cultivate individual-level behaviors with top-down paths; and how these cross-level paths can create nonlinear effects that impact the firm's responses to dynamic changes. These attempts help address the issues of strategy planning and enterprise transformation with the coevolutionary process. Research in this context can facilitate further practical research.

Theoretical Foundation

Complex Adaptive Systems

With the increasing complexity of alignment issue, the alignment of business and IS becomes a Complex Adaptive System (CAS). As a branch of complexity science, CAS provides a way of thinking about systems as being comprised of agents that interact with each other and behave according to defined rules (Onik et al., 2017). CAS acts as a medium to produce emergent complexity of an organization. In general, CAS is nonlinear that agent interactions make holistic behaviors more complex than can be predicted by summing individual behavior (Tivnan, 2005). Besides, CAS presents diversity because each agent is different from the others and its performance depends on the other agents and the system itself (Tivnan, 2005). However, CAS can still be self-organized in that new behavior patterns appear as consequences of agent interactions (Nan & Tanriverdi, 2017). Although posing between regions of order and chaos, CAS create order in the process of evolution (Benbya & McKelvey, 2006b). Currently, the CAS theory has been widely applied to research domains of organization (Holland, 1995; Tivnan, 2005) and IS (Benbya & McKelvey, 2006b).

Recently, scholars argue that the alignment of business and IS displays the features of CAS (Tanriverdi et al., 2010; Vessey & Ward, 2013). This kind of alignment requires firms' IS strategies, goals, and technologies harmonize with business strategies and goals. The firm's alignment issue becomes unapproached as firms face the challenges of "dancing rugged" markets (Tanriverdi et al., 2010), pervasive digital technologies (Yoo et al., 2012), and a manifold of interdependent relationships (Allen & Varga, 2006). Uncertainties and non-linearity have been imposed on the alignment issue. For example, bottom-level informal behaviors make organizations hard to be managed, such as human inertia and unpredictable errors (Benbya & McKelvey, 2006a). Instead of pursuing a fixed alignment solution, potential deviations from intended plans need to be "captured" and "tamed" (Tanriverdi et al., 2017). A temporary misalignment state may also have beneficial effects (e.g., IT ecosystem) (Baker & Singh, 2015). Facing with unpredictable changes, the alignment order is more difficult to create than traditional alignment (Tanriverdi et al., 2017).

Coevolution is a principal order-creation mechanism (McKelvey, 1999; Lewin & Volberda, 1999). For external or internal organization, the coevolution aims to capture its fitness landscape and to seek for dynamic suitable positions (Kauffman, 1993). The business and IS coevolution forms "a co-evolutionary process that reconciles top-down 'rational designs' and bottom-up 'emergent processes' of coherently interrelating all components of the business/IS relationships in order to contribute to an organization's performance over time" (Benbya & McKelvey, 2006a). Similar to the nature selection process (variation, selection, retention) (Cecez-Kecmanovic, 2001) and the dynamic capability process (sensing, seizing, transforming) (Teece, 2009, 2014), the coevolution theory helps to illustrate how the coevolutionary process can shape long-term alignment trajectories and create orders with the help of coevolutionary principles.

Agent-Based Modeling

Exploring holistic effects of CAS from individual behaviors is beneficial to capture and control the complex phenomena. The CAS theory relies on three key constructs to describe nonlinear causality: agents, interactions of agents, and the environment (Nan & Tanriverdi, 2017). Specifically, each agent exhibits its behavior rules to continuously reconfigure itself according to what is rewarded by its surroundings (Nan & Tanriverdi, 2017). Agent-based modeling (ABM) is a technique that allows us to explore how the interactions of heterogeneous individuals impact on the wider behavior of social/spatial systems (Crooks, et al., 2017). ABM requires each agent behave in a stochastic, nonlinear manner, and possesses a nonlinear capacity to adapt over time (Tivnan, 2005). As a "bottom-up" modeling method, it describes emergent behaviors on the individual level, and the whole organizational behaviors can emerge as a cumulative outcome of individual behaviors. It explains the actions and interactions of agents with a view to assess their effects on the system as a whole, such as the NK model (Kauffman, 1993). In this case, ABM will be able to capture detailed real-life phenomena (Borshchev and Filippov, 2004) and generate micro controls for detailed decision-making within coevolution.

Literature has considered applying ABM to the coevolution of business and IS alignment. For example, Merali (2012) focuses on interactions among IS agents to explain how coevolution at a higher level emerges and posits that ABM represents an appropriate investigation for understanding bottom-level behaviors. Considering organizations are flooded with interactions of agents (Allen, 2006; Vessey, 2013), some scholars claimed that ABM is a suitable way to understand, validate, and further refine the theory ideas of organizational coevolution (Vidgen & Wang, 2006; Benbya & McKelvey, 2006b; Tanriverdi & Lim, 2017). Furthermore, an agent-based framework is proposed to define the mechanisms that are necessary for successful coevolution (Allen, 2006).

Up to the authors' knowledge, none of the extant coevolutionary studies of alignment have developed a specific ABM to explain the bottom-level behaviors and their impacts on corporate strategies. To describe the alignment complexity and predict the alignment trajectory smoothly, we develop an ABM of an illustrative organization in this paper.

ABM of Business and IS Coevolution

ABM Design

In this article, we take a hierarchical organizational structure as an illustrative example. This example aims to absorb the external changes and to form coevolutionary alignment, as in Figure 1. The external changes are multilevel and can act at different layers of actors. This structure is assumed with layers of presidents, business/IS managers, and business/IS actors. Generally, the structure can recognize and handle external changes through reporting and commanding flows among layers (as thick solid arrow in Figure 1). This acts as a rational top-down planning process. Beyond this, the agents can display different kinds of behaviors to absorb the changes (e.g., communicating, knowledge sharing, knowledge learning), which presents the bottom-up adaptation. For example, agents can communicate with each other to exchange information, share knowledge on the basis of the communicating behaviors or the databases; and also learn knowledge from external information. Through continuous top-down planning and bottom-up adapting, the organization can absorb external changes and co-evolve business and IS towards the same direction.

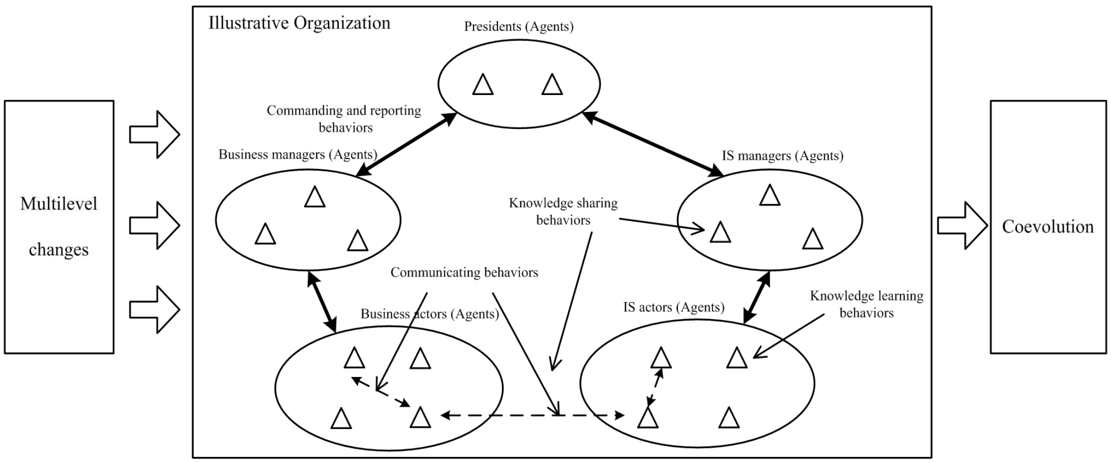

Figure 1. Overview of our theoretical model

Our ABM design is based on a well-established approach that uses strings of digits to represent the behaviors of agents. Figure 2 depicts the key components of our model, which are described in detail below.

(1)Environment

Currently, organizations operate in a world that is increasingly permeated with digital technologies (Yoo et al., 2012). The pervasive digital innovations (e.g., component IT innovations or architectural IT innovations) are radically changing the nature of products and services (Gawer & Cusumano, 2014), and have toppled the traditional assumptions of partnerships, supply chains, and inter-firm collaborations. For example, the ios headed operating systems drive the IT trends convergent and generative (Yoo et al., 2012). Consequently, business and IT environments have become hyperturbulence and unpredictable. In such a dynamic environment, changes may occur in any layers of the organization. For the sake of simplicity, multi-level changes are immediately added to the ABM model. To explain the changes' impacts on agents, we argue that one knowledge set (Joseph et al., 2014) can be imposed on effected agents. For example, we assume that each change can bring 5 new knowledge points (one knowledge set). This knowledge set needs to be spread and accepted by all of the agents, and thus coevolves business and IS domains.

(2)Agents

We view all of the presidents, business/IS managers, and business/IS actors as agents. For example, we assume that the illustrative organization consists of 1 president, 10 business managers, 10 IS managers, 50 business actors, and 50 IS actors. Additionally, we can divide the managers and actors of each domain into 3 groups, and the group of business or IS actors is charged by its higher-level group of business or IS managers. To describe external changes, we deem that each agent's attributes are characterized by a bundle of knowledge points that describes its understandings about the changes. For example, if one change occurred in the field of business actors, one of the agents of business actors may display its attributes as [1 1 1 1 1], while the attributes of other agents may be [0 0 0 0 0]. A value of 1 indicates that the agent has grasped the knowledge point while a value of 0 indicates the contrary. In our ABM, we assume that there will be 5 changes which separately occur in the 5 fields. Therefore, the length of any agents' attributes is 25. In terms of the above explanation, the numbers of agents, groups, changes, and the length of one knowledge set are not meant to represent reality in a strictly quantitative sense; instead, they are chosen for their effectiveness in generating theoretical insights.

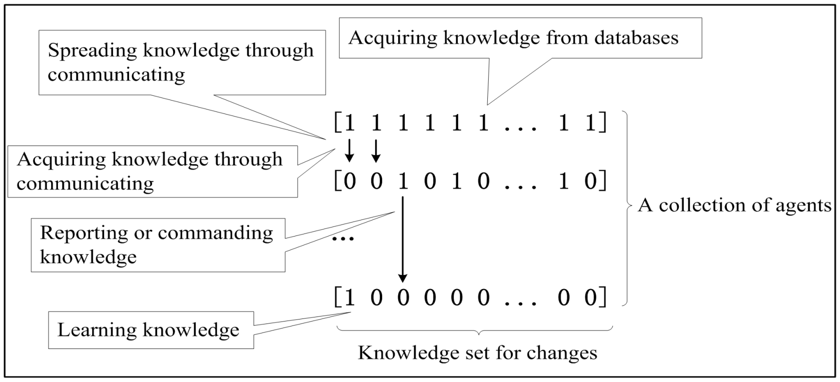

Figure 2. Knowledge dissemination in our model

(3)Behavioral rules

Behavioral rules guide an agent's search for the desired understanding of input changes by preserving or changing values of digits in its string (Nan & Tanriverdi, 2017). According to our previous work, we list 5 behavioral rules that could absorb the knowledge points of changes. The data appeared in this section can also be validated through sensitivity analysis.

The first behavioral rule of any agent is its communications with other agents. In each simulating tick, an agent (e.g., presidents, managers, actors) could select partners and, via communicating, passes one knowledge point he knows (digit that is 1) or receives one knowledge point his partners know. We believe that agents in the same group take a higher probability of knowledge exchanging ($p = 0.8$) than that in the same domain ($p = 0.4$), and even higher than that in different domains ($p = 0.1$). However, if the organization encourages mutual-communication or knowledge sharing activities, the probabilities of knowledge exchanging among different domains will rise. Furthermore, we also consider the path dependency factor, which means, if two agents have successfully exchanged knowledge before, their probability of knowledge exchanging for the next time will increase 0.1, conversely, if they have failing passed knowledge before, the corresponding probability will decrease 0.1 for the next time.

The second behavioral rule of an agent is obtaining knowledge points from databases. We assume that each agent's initial probability of knowledge elicitation from databases is 0.1 in our ABM. If the organization encourages the knowledge sharing activities from databases, this probability will rise. Similar to the first rule, each successful knowledge elicitation from databases will increase the agent's probability by 0.1, while the failing elicitation before will decrease by 0.1.

In order to obtain the other domains' knowledge proactively, there is another rule by learning from external information. With additional information, an agent is likely to sense the future actions caused by other domains. We assume that each agent's probability of knowledge acquisition by learning is 0.1, but it will rise if an organization enhances the learning capability. The knowledge acquisition probability will also be increased or decreased on the basis of the previous records.

The other two behavioral rules of agents are reporting action and commanding action. The reporting action refers to transfer the knowledge points of changes to an agent of the upper layer. The precondition of this action is that all of the agents in one group of the lower layer should have grasped the knowledge set of one change. For example, if one change occurred in the field of one business actor group, this group should report this change to one superior business manage only after this group has totally grasped the knowledge points of this change. The commanding action refers to transfer the knowledge points of changes to all of the agents in the lower layer. A precondition is that one change has been totally understood by the upper layer. It is worth noting that the acceptance rates of the commands are different with agents. In our ABM, the agent who has previously obtained knowledge points of one change could accept the corresponding command more easily than those agents know nothing of this change.

(4)Performance outcomes

Performance outcomes refer to evaluation indices of the ABM. The complexity of performance induced by multilevel changes may be captured by the overall distribution of knowledge strings in our ABM. To embody the performance, we introduce three indices from different perspectives. The first is misalignment, which refers to the inefficiencies, difficulties, inabilities concerning the alignment of business and IS (Carvalho & Sousa, 2008; Őri., 2014). Scholars argued that organizations are continually suffering from misalignment while they address alignment achievement (Chen et al., 2005; Carvalho & Sousa, 2008; Őri., 2014). A misalignment state may damage overall performance advantages (Őri., 2014). From the viewpoint of knowledge, we view the misalignment as the knowledge distance between business domain and IS domain of the organization, which is similar to the matching and moderation approach (De Haes, 2015) in the traditional alignment research. The formula of this metric is in the following, where *n* shows the number of changes and 60 is the number of agents in the business domain or IS domain.

$$Misalignment = \sqrt{\sum_{i=1}^{5n}((\sum_{j=1}^{60} B_{ij})/60-(\sum_{k=1}^{60} IS_{ik})/60)^2} \quad (1)$$

However, according to the emergent complexity, displaying a misalignment doesn't always exhibit a decrease in organizational performance, and occasionally may even be opposite (El Sawy et al., 2010). Scholars have started to question the fidelity of alignment in performance improvement (Tallon et al., 2011; Liang et al., 2017). Baker (2015) argued that practitioners should carefully consider the benefit that innovations offer, even though they lead to a temporary misalignment. Therefore, we assume that the impact that changes (e.g., IS innovations) bring to an organization displays a performance growth curve. Which means, the performance may increase initially and then stabilize with the input changes. A typical growth curve formula is adopted in our ABM (Zwietering et al., 1990). Meanwhile, we also consider the misalignment factor in this metric. We argue that the misalignment state may influence the growth curve and increases its uncertainty. We name this metric as adaptation, which represents the adaptive capability of the organization. According to formula 2, the numerator depicts a growth curve that depends on the number of changes (n), T refers to the simulation time. Because the misalignment value may be 0, we consider an exponent in the denominator. With this formula, the changes can increase the performance while the misalignment may act adversely.

$$Adaptation = (\frac{5n}{1+10e^{-0.5T}})/e^{Misalignment} \quad (2)$$

We also consider the cost consuming in the organization's evolutionary process. This factor should always be noticed when analyzing the alignment issue (Luftman, 2004). In our ABM, each kind of behavioral rules may produce a cost. The knowledge dissemination in the organization is at the expense of kinds of consumption, such as the media, printings, and labor. Reasonably, we assume that the costs of the reporting and commanding actions (cost = 20) are higher than that of the other three rules. With regard to the communication rule, we believe that the communicating cost in one group (cost = 1) is lower than that in one domain (cost = 2), and lower than that between different domains (cost = 4). Furthermore, the cost of sharing knowledge (cost = 1) is lower than the cost of learning knowledge (cost = 3). These data is validated by sensitivity analysis. The overall cost can be acquired by continuously executing the behavioral rules. Considering the cost metric, the organization may restrict its adoptions of the three principles.

In general, the alignment issue could be situated in strategic alignment, structural alignment, social alignment, and so on. The social alignment refers to the mutual understanding of business and IT executives and their commitment to plans, objectives and mission. According to the above modeling components, our ABM describes the social aspect of business and IS alignment, which is the most unapproachable and unpredictable factor in the long run of organization evolution. Our ABM aims to capture the social behaviors in the bottom level and explore how to control these behaviors to reach a superior coevolutionary process.

ABM Experiment

All of the agents were created at the beginning of a simulation session. Their group numbers were randomly determined. And their attributes were also initialized according to the input changes. A simulation session may take hundreds of clock ticks until the organization totally absorb the input changes. Each clock tick includes two specific steps. Firstly, each agent has an opportunity to pursue knowledge points by randomly executing the first three behavioral rules. Based on the behavior rules, this step mainly determined the probabilities of knowledge acquisition of agents. Secondly, the organization determined whether should execute the reporting actions or commanding actions. Three performance metrics were calculated at the end of each clock tick. The pseudocode is in the following. As our ABM ran through a sequence of clock ticks, we obtained a time path of performance ranking changes. The three kinds of time paths help us analyze the performance difference under various conditions. The ABM was implemented using the NetLogo toolkit (Nan & Tanriverdi, 2017). The simulating process was displayed in Figure 3, which shows the agents' interactions in the left panel and the organization performances in the right panel.

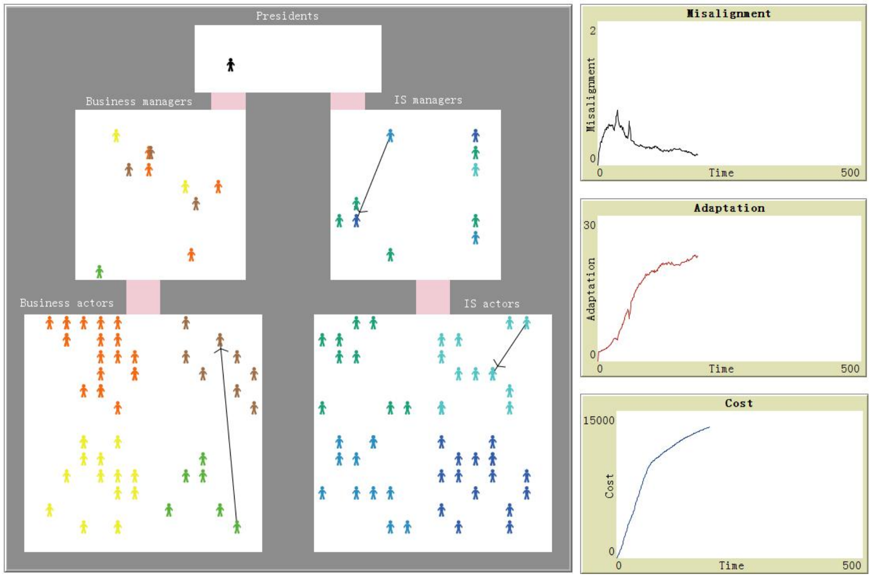

Figure 3. ABM experiment process

Let the model user set parameters
Setup {
Setup-patches
Setup-agents }
Setup-patches {
    Ask each patch [Set color] }
Setup-agents {
    Create agents [Set color, group number, knowledge set, coordinate] }
Run one tick of the model clock {
    Random Mutual communication, Knowledge sharing, Knowledge learning
    Report
    Command
    Fitness }
Mutual communication {
    Random exchanging knowledge [Set probabilities] }
Knowledge sharing {
    Random sharing knowledge [Set probabilities] }
Knowledge learning {
    Random learning knowledge [Set probabilities] }
Report {
    Set knowledge
    Set cost }
Command {
    Set knowledge
    Set cost }
Fitness {
    Misalignment

	Adaptation Cost }

Overall, with regards to the complexity and uncertainty in traditional alignment, the above ABM development and experiment focus on agent interactions and knowledge spreading, provide an approach to describe the business and IS coevolution process, and helps validate coevolutionary behaviors and guide organization evolution in the next step.

Discussion and Conclusion

This paper is a further exploration in addition to our previous coevolution review and system dynamic researches. Given the emergent complexity in the alignment ecosystem, this paper contributes in the following ways: first, the quantitative view of the coevolutionary research helps improve the precision of previous theoretical development, and better describes the long run of coevolutionary landscape; second, this paper lays emphasis on social alignment and individual interactions, which combines the top-down design and bottom-up adaptation. Overall, this paper helps pave an application way for displaying coevolutionary trajectories and offering evolutionary guidelines for organizations.

Theoretically, this paper represents the features of multilevel effects, multi-directional causalities, and path dependencies in the process of theoretical and model developments. The ABM exhibits the top-down planning (reporting and commanding actions) and bottom-up adaptation (communicating, knowledge sharing, knowledge learning), which offers guidance to explore and validate other behavior rules. Practically, through simulating the model experiment, the ABM of this paper helps explain the organization evolution process, create alignment orders, and provides a better support for organization transformation.

This paper still presents limitations. First, according to the literature of coevolution, other behavior rules (e.g., seeking for modularity, improving internal complexity) need to be considered in our ABM. Taking modularity as an example, knowledge points may be composed as a modular that can be sent or received at the same time. Second, synergistic or conflicting relationships may exist between external changes, which may influence the compositions of agent attributes and the dissemination of knowledge points in our model. Third, our ABM needs involve other performance metrics (e.g., alignment maturity) or other alignment dimensions (e.g., structural alignment) when considering the traditional alignment research.

The above limitations drive future research suggestions. First, other behavior rules can originate from coevolutionary principles and be added to the ABM. Second, the synergistic or conflicting relationships among changes can be reflected on the ABM development and experiment. Third, we argue that the achievements of traditional alignment research should be combined in searching for the coevolution of business and IS. Organizations should take account of the balanced alignment and unbalanced coevolution in the long run. A sensing capability may be considered to identify the complexity regions in advance (Tanriverdi & Lim, 2017). If the complexity of organizations or markets is low, traditional alignment mechanisms, models, and performance metrics should be adopted to seek sustainable competitive advantage. And if the complexity is high, multiple coevolutionary principles should be introduced to address the nonlinearity and uncertainties. Organizations need to pursue temporary and fleeting advantages in the rugged landscapes.

Overall, with the advent of emerging technologies and the associated dynamic strategies, complexity is likely to pose a long-term challenge to analyze alignment. Recent research on coevolution has expanded our research horizons. The theoretical and ABM developments here provide a bridge for researchers to integrate theory into practical applications, so that practitioners can eventually achieve business success with the help of dynamic business and IS alignment.

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