2528-9705

Örgütsel Davranış Araştırmaları Dergisi
Journal Of Organizational Behavior Research
Cilt / Vol.: 3, Sayı / Is.: S2, Yıl/Year: 2018, Kod/ID: 81S245

AN ECOLOGICAL MODEL FOR KNOWLEDGE MANAGEMENT BASED ON THE INTERACTION WITHIN ECOSYSTEMS

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ABSTRACT

Aim: This study presents an ecological model for knowledge management based on the integration and development of three management approaches: digital business ecosystem, value creation ecology and social, mobile, analytics, cloud and Internet of things (IOT) ecosystems. Design / Methodology / Approach: A correlation was firstly established between the digital business ecosystem and the social, mobile, analytics, cloud, and IOT ecosystem with value-creating ecology. Once this correlation has been confirmed, then the relationship between them is measured. This research used meta-analysis methodology. Findings: An ecological model for knowledge management has been derived from the integration of three management approaches. Furthermore, value-creating ecology promotes interaction between the digital business ecosystem and social, mobile, analytics, cloud and IOT ecosystems. Practical Outcomes: Knowledge Ecology Management (KEM) is the process of creating, sharing, applying and managing knowledge ecology. Knowledge ecology is the framework of an integration of knowledge of people operating in various industries. Social implications: Knowledge Ecology Management is primarily focused on social networks. Utilizing the knowledge of those operating in these social networks with diverse fields of expertise can contribute to the growth, development and diversity of knowledge. Originality / Value: Knowledge Ecology Management creates the value mediated by interaction of ecosystems via value-creating ecology.

Keywords: *Digital Business Ecosystem, Value Creation Ecology, Ecosystem – Ecosystem Interaction, SMACIT (Social, Mobile, Analytical, Cloud & Internet of Things) Ecosystem, Knowledge Ecology Management (KEM).*

INTRODUCTION

This paper represents the knowledge ecology management model based on the integration and development of three management approaches: digital business ecosystem, value creation ecology and SMACIT (social, mobile, analytics, cloud and Internet of things (IOT) ecosystems. Knowledge ecology management (KEM) refers to the process of creating, sharing, using and managing the knowledge and information ecology of organizations operating in different industries. Ecology has been applied as metaphorical term for viewing information systems in organizations (Davenport and Prusak, 1997). The balanced and adapted management of explicit and tacit knowledge is said to lead to Knowledge Management Ecology (Despres and Chauvel, 2000). Knowledge ecology primarily focuses on social networks of individuals and thus seeks to create more diversity in knowledge. A knowledge ecology environment is impacted by sudden and pervasive change. Knowledge ecology is made up of knowledge nodes and knowledge exchanges or knowledge flows. In the knowledge ecology the basis for cooperation and survival is differentiation and similarity between the knowledge nodes (Malhotra, 2002). The companies positioned at the leading edge are using

Geliş tarihi/Recieved: 19.12.2017 – Kabul tarihi/Accepted: 04.02.2018 – Yayın tarihi/Published: 21.08.2018

today the Digital Business Ecosystem (DBE) in order to support creating valuable knowledge. In this context, in order to support the valuable knowledge creation, organizations obsessed with extracting and measuring knowledge must shift the focus of their knowledge initiatives to developing an open culture of communication and collaboration that is supportive to the sharing of innovative work and business (Maracine and Scarlat, 2009). An ecosystem implies that``everything is connected to everything; everything feeds back through the ecosystem on itself. The interconnectedness preserves the overall system". Ecosystems evolve through adaptation of living organisms to their environment (Papaioannou et al., 2009). An organizational ecology is a combination of intangible relationships among people, practices, policies, daily experiences, and various forms of knowledge (Bennett and Bierema, 2010).

In recent years, there has been an increasing amount of research conducted on the convergence of mobile computing, cloud, analytic, and social (Roberts, 2011; Hurbean and Fotache, 2013; Raman, 2016). Five key areas of Social media, Mobile systems, Analytics, Cloud, and IoT (SMACIT) have been recognized as significant drivers for enterprise digital developments (Akoka et al., 2017) . Through expanding opportunities via a variety of information technology infrastructure, social media supports organizational knowledge management; cloud computing expands the boundaries of organization's knowledge management in such a way that it utilizes the knowledge of individuals other than employees of the organization; mobile technologies means that employees have constant access to advanced KM tools, creating “always on” KM.; provide analytical, insight and feedback capabilities that enable employees to work better together (Kane, 2017). Separately, a lot of researchers also examined the correlation between each of social, mobile, analytics, cloud, and Internet of Things ecosystems with the digital business ecosystem. For example, these researchers analyzed the relationship between social ecosystems (Attour and Peruta, 2016; Kache et al., 2017), Mobile Ecosystems (Lee and Kim, 2017; Majava et al., 2016), Analytical Ecosystems (Kache et al., 2017; Zimmermann et al., 2016) and cloud ecosystem (Sun et al., 2016; Mitra, 2017) with the digital business ecosystem. Furthermore, due to the nature of the IoT ecosystem in which firms must collaborate with competitors and across industries, it is easy to see why traditional business models are not adequate (Chan, 2015). IOT ecosystem provides a wide variety of data and makes use of various tools for data collection; for example, sensors are among one of the tools used by Internet of Things ecosystem to collect data. Collected data is then transmitted to the analytical ecosystem by theses sensors (Sheng et al., 2015). Therefore, it is evident that there is a relationship between SMAC ecosystem and IOT ecosystem resulting in SMACIT.

However, there is a question here: What is value creating ecology? What is its value? In other words, can Porter's Model of close supply chains (extreme pairs) (Mucciarelli et al., 2017) be a good basis for the interaction within the ecosystems? While, in essence, ecosystems are poor pair networks (Dini et al., 2008). Hearn (2006) presents the metaphor of a “value creating ecology for nonlinear and weak pair of value chains adequate for linkage in ecosystems. In fact, value-creating ecology is a network-driven value chain based on knowledge (Hearn et al., 2007). He also puts an emphasis on the use of value-creating ecology for the interaction within the ecosystems (ecosystems - ecosystems). Therefore, this paper focuses on the value-creating ecology approach as the basis for the interaction within the ecosystems. Despite numerous papers and studies on the relationship between ecosystems, so far no study has yet been found focusing on the value of interaction of social, mobile, analytics, cloud and IOT ecosystems as a whole with the digital business ecosystem. There has been also no study investigating the interaction among social, mobile, analytics, cloud and IOT (SMACIT) ecosystems together. Therefore, this paper aims to initially measure the interaction of digital business ecosystem with the SMACIT ecosystem and the correlation between the digital business ecosystem and the SMACIT ecosystem with value-creating ecology; once it has been confirmed, then the correlation between the digital business ecosystem and SMACIT ecosystem is measured. This research utilized mixed and meta-analysis methodologies incorporating qualitative and quantitative analysis.

REVIEW OF LITERATURE

The network is itself knowledge, not in the sense of providing access to distributed information and capabilities, but in representing a form of coordination guided by enduring principles of organization.(Kogut, 2000). The ecology metaphor has been previously used to describe the use of knowledge within organizations. Specifically, the term knowledge ecology has been used to illustrate how ideas are exchanged, innovations blossom, value is added to information, and new knowledge is tested and applied through accrued expertise and learning and within the rich perspective of the ecosystem (Petrides and Guiney, 2002). Knowledge or innovation ecology refers to ``the set of individuals usually working within organizations who are repositories and generators of existing new knowledge (Metcalfe and Ramlogan, 2008). More recently, there has been some shift in the academic and policy debate on innovation from a more traditional systems approach to ecologies and/or ecosystems. The latter are concepts transferred from the world of biology to the social world in order to explain the evolutionary nature of interrelations between different people, their innovative and their environment measurements (Papaioannou et al., 2009). Berkes (2009) believes that various levels of organization from local to international have comparative advantages in generating and transferring knowledge gained at different scales. International organizations provide an association for interaction among various forms of knowledge. The components of the model and their interaction are discussed below.

SMACIT ecosystem (*Social, Mobile, Analytics, Cloud,* and Internet of Things)

Social, mobile, analytics, cloud and IOT ecosystems have been integrated together and developed "SMACIT" term. Social computing ecosystem encompasses a broad spectrum of social world and machine-centric computing. Therefore, a social computing ecosystem can be used as an umbrella term to describe several paradigms (Hanna et al., 2011; Lugano, 2012). Murphy and Salomone (2013) offered a typology for 2.0 firm and maintain that communication / interactive performance in relation to talented experts will lead to the development of social ecosystems.

The prevalence of mobile phones has led to an explosion in the amounts of human mobility data stored in the cloud (Barak et al., 2016). Basole (2009) defined a mobile ecosystem as an extensive and complex network of heterogeneous actors (both public and private) who interact with each other, directly or indirectly, to deliver mobile products and services to customers. According to Calheiros et al., (2011), market is a crucial component of the cloud computing ecosystem; market is a crucial component of the Cloud computing ecosystem; it is necessary for regulating Cloud resource trading and online negotiations in a public Cloud computing model, where services are offered in a pay-as-you-go model. Besides, Basole (2009) maintains that cloud computing ecosystem provides market space for ecosystem interactions. The mobile ecosystem is characterized by a large and complex network of companies interacting with each other, directly and indirectly, to provide a broad array of mobile products and services to end-customers. Establishment of strong relationships with key stakeholders in different enterprises develops an analytical ecosystem in business (Davenport & Harris, 2010). New important players are emerging, and the scope of the mobile ecosystem is expanding and encroaching on the technological boundaries of other IT (Lee & Kim, 2017). Measurement tool analysis allows user to experience an application and is considered a key component of the mobile ecosystem (Ivan & Popa, 2014). In addition, a wide range of mobile ecosystems often involve several common value networks, implying that ecosystem boundaries disappear and different ecosystems converge within a new ecosystem as well as new business model (Basole & Karla, 2011). Mobile cloud computing is considered as a development of cloud platform. Mobile cloud computing can be viewed as a cloud infrastructure enhanced to provide a mobile ecosystem for mobile apps and to allow access to business apps from mobile devices. The data processing and the data storage happen outside the mobile device, and results are displayed through the mobile device screen or speakers (Velev, 2014). The role of advanced ICT trends known as SMAC solutions new models of organization operations on the global markets using strategic resources, such as the knowledge supported with SMAC solutions (Adamczewski, 2016). The comprehensive SMACIT ecosystem theme has been presented in Table 3. IOT ecosystem is connected to SMAC ecosystem via cloud computing (Parygin et al., 2017) and analytical computing (Sheng et al., 2015).

Characteristics of Value Creation Ecology (VCE)

According to Allee (2000), one of the fundamental issues in a knowledge-based economy is value creation. Supply chain and value chain are the traditional answer to this question, but a knowledge-based economy requires moving towards web value or network value.
A value network generates economic value through complex dynamic exchanges between one or more enterprises, customers, suppliers, strategic partners and the community. A knowledge-based economy can become further developed through redesigning the supply chain business into a business based on a value network with a more fluid structure. Knowledge value is one of the key components of the value network. From evolving knowledge ecology, increased competition and expansion of the economy made it necessary to focus beyond the enterprise itself in order to learn more about one's market, one's industry, one's consumers (Laszlo and Laszlo, 2002). In other words, ecology focuses on more than one market, customer, and an industry. According to Hearn's theory (2006 & 2007), there are fundamental changes in five areas in the application of value-creating ecology metaphor rather than value chain.
These changes are:

I. Co-Creators of Value: value creation is not a simple one-way linear process but involved processes of reiteration and feedback."
II. From product value to network value: value is created and extracted from a network of relationships and values can be generally understood as a function of the entire network.

III. From mere cooperation or competition to complex Co-opetition: Co-opetition is the combination of competition and co-operation processes (see also Carayannis et al., 2014).
IV. From stand-alone strategic thinking to strategic thinking of ecology as a whole: the need to pay attention to the whole value ecosystem when a strategy develops.
V. Main idea: from the supply chain (or value chain) to value ecology.

Therefore, if we agree with all these changes and the viewpoint of Davenport and Prusak (1997) that ecology serves as a metaphor for the use of information technology and information systems throughout the organization and especially Kogut belief (2000) that " The network is itself knowledge", so we can infer that knowledge is the key driver for value creating ecology (see also Hearn (2006). Moreover, a change in supply chain to value creation ecology leads to formation of co-creation ecology, customer ecology and coopetition ecology in the organization. As a result, the term "knowledge ecology" emerges. In this paper, knowledge ecology management is derived by integrating three management approaches.

Digital Business Ecosystem (DBE) and Value Creation Ecology (VCE)

Business ecosystem is the extended concept of biological ecosystems not implying that business networks are ecosystems or they should act like biological ecosystems. Business ecosystems are characterized by a large number of loosely interconnected participants who depend on each other for their mutual effectiveness and survival" (Iansiti and Levien, 2004a). Furthermore, Iansiti and Levien (2004b) define business ecology as: "... Rather than involving individual companies that are engaged in technology races, battles in the future will be waged between ecosystems or between eco- system domains. "The Web of Life" is another term for ecology and is another word for the web. Therefore, the ecology model is a dynamic and multi-directional cluster of networks. Knowledge and shared knowledge are the key drivers of knowledge in value-creating ecology (Hearn and Pace, 2006). The knowledge ecology model portrays the knowledge ecosystem of organizations, defining knowledgedistribution, interaction, competition and evolution to describe the structure of knowledge assets in organizations from an ecological view (Chen et al., 2010). Clarysse et al (2014) also found that network is almost 100% publicly backed and fails to bridge the knowledge and business ecosystem. There are several knowledge can be explored and represented in creating value ecology: the emergence of knowledge, differentiation between knowledge and knowledge evolution (Carayannis et al., 2014). Table 3 below presents the main categories and themes related to the value-creating ecology.

The relationship of (SMACIT) - social, mobile, analytical, cloud and IOT ecosystem and value creating ecology

The dynamic development of ICTs in recent years has popularized the third platform, which is also described as SMAC (Social, Mobile, Analytics, Cloud). SMAC is a unique IT ecosystem solution that creates a new knowledge and business model based on information from the business environment (Adamczewski, 2016). In addition to value creating ecology, SMAC (Cornelius, 2013) and IOT ecosystems are other mainstream approaches that the researchers add to the digital business ecosystem. There is an ecological link between SMAC and VCE. Finin et al. (2008) investigated the Information Ecology of Social Media and Online Communities.

As an example of customer's participation in the knowledge ecology creation chain, Motiwalla (2007) maintains that m-learning intersects mobile computing with e-learning;

it combines individualized learning with anytime and anywhere teaching and provides the ability to support students participating in social education programs. The Ecology of Mobile Commerce: charting a course for success using value chain analysis (Motiwalla and Strader, 2003). The application of an ecological analytical framework for data formed in relation to ecological planning frameworks can be valuable (Robertson & Wilson et al., 2009). Experimental work is characterized by a high degree of control over unwanted variability is a powerful scientific strategy to understand ecological phenomena. In this tradition of 'analytical ecology,' uncertainty is undesirable, and is eliminated where possible (Fischer et al., 2009). The idea behind the development of cloud computing ecosystems is to guide and support cloud model development and cloud service and cloud protocols management represent a hybrid cloud environment (Lan et al., 2013). In the cloud ecosystem, in fact, capital and population play as hosts and parasites: the networked structure of the society, i.e. population, feeds on the huge corpus of capital and as a result it will lead to the capital increase by the same population (Dovey, 2014). To build a sustainable IOT ecosystem, a full multi-dimensional study is vital for understanding IOT ecosystem (Shin and Jin Park, 2017).

Features of Digital Business Ecosystem (DBE)

The notion of Digital Business Ecosystems (DBE), which has been proposed by Briscoe (2010), makes it possible to understand the different classes of digital business ecosystems using agent-based modeling, complex adaptive systems, and characteristics of biological ecosystems, to construct their counterpart in digital ecosystems. A digital business ecosystem can therefore be identified through the following features (Graça and Camarinha-Matos, 2017):

A digital business ecosystem can therefore be characterized through the following attributes:

I. Economy: the counterpart of environment, i.e. the economy of society, combining concepts of the business and social ecosystems;
II. Business: the concept of business ecosystem is adopted, where the agents are the businesses which influence and are influenced by the environment;
III. Population: the concept of business ecosystem is adopted, i.e. the interacting organizations and individuals (consumers, suppliers, competitors, and other stakeholders), who coevolve their capabilities and roles;
IV. Community: the concept of social ecosystem is adopted to represent a social unit that shares common values (Tvarozek and Jurkovic, 2016)
V. Multi-agent system: a multi-agent system contains an environment, objects and agents (the agents being the only ones to act), relations between all the entities, a set of operations that can be performed by the entities and the changes of the universe in time and due to these actions;
VI. Ecology: the concept of biological ecosystem is adopted (Rincon et al., 2016).
VII. Evolution: the concept of business ecosystem is adopted, and the evolutionary theory of expertize and behavior of business organizations is applied;
VIII. Topology: the concept of digital ecosystem is adopted. The participants are connected through a digital network supported by ICT technologies.

The members are connected together through a digital network, a network that is supported by digital technologies. As is evident, MASs is a feature of DBE.

Interaction between ecosystems to manage knowledge ecology (Knowledge Ecology Management)

Social computing technology could be used as building blocks for knowledge sharing (Ray 2014). The vast evolution of Social Computing in the last years and the tremendous improvement of novel technologies including cloud computing, open source technologies, recommender systems, personalized knowledge management systems, Big Data Systems, and Open Educational Resources approaches to collaborative learning (Lytras et al. 2015).

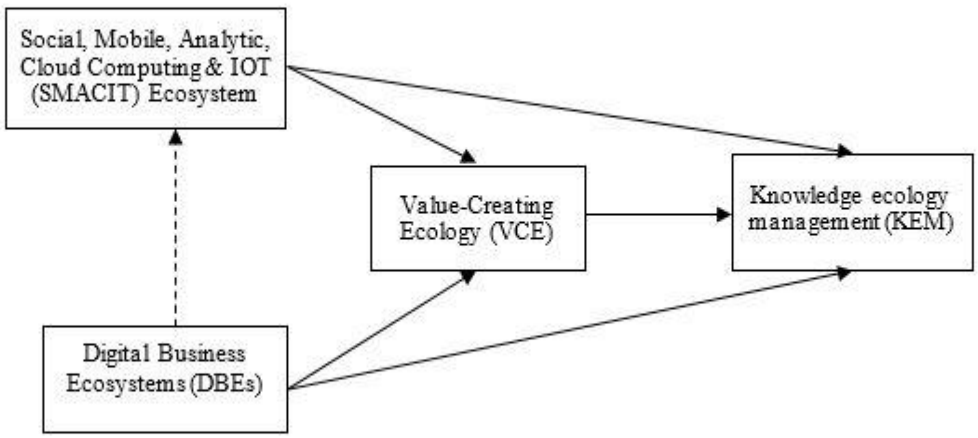

Figure 1: The relationship between the main categories of the model

In many ways, mobile social media is a KM system ideally suited for leaking knowledge (Leonardi, 2017). Collaborating Social media with mobility can be a new horizon for people interaction and its transformation of knowledge can be well accessed with Analytics and Cloud computing for generating a timed and better result for the customers who are seeking right product on right time (Srivastva and Kiran, 2016). It is these knowledge flows that enable a technological platform to move up from supply-chain to industrial platform, contributing to the emergence of a digital business ecosystem (Attour and Peruta, 2016). Therefore, the knowledge ecology management model is derived from the relationships between the three management approaches (Fig. 1). Although some studies done on Knowledge Ecology Management (Davenport and Prusak, 1997, Despres and Chauvel, 2000, Jiandong, 2009, Chen et al., 2016), knowledge ecology management has not yet been studied using three management approaches including BDE, VCE and SMACIT. In this paper, knowledge ecology management will be achieved through the interaction of the digital business ecosystem with the SMACIT ecosystem mediated by value-creating ecology.

METHOD

The explicit use of both quantitative and qualitative methods in a single study, a combination commonly known as “mixed method” research, has become widespread in many of the social sciences and applied disciplines in the past 25 years (Maxwell and Loomis, 2003). Meta-analysis has become a standard way of summarizing empirical studies in many fields, including ecology and evolution (Nakagawa et al., 2015). The main questions in the qualitative analysis that the researchers are trying to answer are: Is there any correlation between the DBE and SMACIT categories mediated by VCE? Is it possible to provide a theme as the output of the qualitative analysis stage? In order to answer these questions, the researchers conducted a quantitative analysis. Does the knowledge ecology management is the result of the correlation between DBE and SMACIT mediated by VCE? Are the concepts used in the theme reliable? Can the structural model of knowledge ecology management be presented if there is a linear relationship between the categories? To answer these questions, the researchers suggested using a mixed methodology. In order to measure the interaction of the digital business ecosystem with the SMACIT ecosystem, the relationship between the digital business ecosystem and the SMACIT ecosystem is calculated by the value creation ecology. Once this connection has been confirmed, the relationship between the digital business ecosystem and the SMACIT ecosystem will then be measured. The following table provides some of the major articles related to knowledge ecology and business ecosystems. Table 1 shows the main theoretical and methodological gap that has not been identified in previous studies (Table 1).

Table 1: Theoretical and methodological gap

Theory & Methodology gap	the reviewed paper	
Based on the idea of Hearn and Pace (2006), Metaphor Value-Creating Ecology (VCE), as a value chain to connect network-enabled and can be used to build ecosystems. This model is presented on the same claim.	Authors picked out five ecological registers: the ecology of the professional self, the ecology of the client relationship, the knowledge ecology of professionalism, the ecology of the professional environment, the discursive ecology of professionalism	Theory (Evans, 2013) Methodology
As shown in Table 3 that's inserted later, through meta-analysis identified combine various spheres of ecology and create an integrated model of ecological knowledge.	The paper first examines some of the earliest work. Using Noordegraaf's three categories, the case is examined as a 'pure', a 'hybrid' or a 'situated' profession.	
This model used of knowledge together as codified and non-codified. But ecological knowledge, in general, achieved with conjunctions DBE, SMAC by VCE.	Maintenance management activities include identifying, creating and storing knowledge assets. The knowledge assets are either documented/codified or undocumented/non-codified.	Theory (Ansari et al., 2014) Methodology
This paper used by textual (Qualitative analysis) and statistical (Quantitative analysis) methods.	In all, 27 SMEs in the area of IT (Information Technology) in Korea were analyzed through interview method basically.	
According to digital business ecosystems theory, in different habitats (Industries) are formed interacting populations of SMEs social knowledge stored on the cloud ecosystem are analyzed (SMAC) and distributed between SMEs communities.	The purpose of this study is to figure out the factors for sustainable growth of small- and medium-sized enterprises (SMEs). It cannot survive if they do not accept open innovation in knowledge strategy and business model.	Theory (Yun et al., 2015) Methodology
In the present study, Dynamic and complex environment created ecological knowledge measured through meta-analysis. Finally,	According to digital business ecosystems theory, in different habitats (Industries) are formed interacting populations of SMEs social	

according to the 120 expert knowledge-based companies, is achieved ecological model of knowledge.	knowledge stored on the cloud ecosystem are analyzed (SMAC) and distributed between SMEs communities.	
Cloud and mobile computing, to build trust and reputation can overcome the knowledge heterogeneity (KH) (Yan et al., 2017). By SMAC, cloud and mobile computing will be added to the DBE.	Building on knowledge-based view and demographic diversity theory, the purpose of this paper is to re-conceptualize knowledge heterogeneity (KH) (i.e. diversity in individual or organizational knowledge) and to explore a broader set of relationships between KH and the multi-dimensional(i.e. dynamics and ambidexterity) innovation.	Theory (Tsai, 2016) Methodology
With in-depth study identified the relationship between the three main categories then with meta-analysis, the themes consist in the qualitative analysis, the quantitative tests. So, despite the difference and heterogeneity of knowledge is obtained integrated model of ecological knowledge.	This paper utilizes an inductive approach that analyzes qualitative materials to construct the essential meanings of intra organizational KH, and to explore the influences KH brings onto the ambidextrous innovation. A four-category typology of KH is emerged.	
The business process on the complex Business environment, many complexities, risk and uncertainty have an Ecological Vision (Lavassani and Movahedi, 2017, Gabriel et al., 2016). The relationship between categories and ecological vision to knowledge for dealing with such situations, The business ecosystem intelligence (Basole et al., 2016) provided.	Organizations and their members operate in increasingly complex, dynamic and even disruptive environments, with risk and uncertainty being major challenges. To that effect, data, information, knowledge, and respective competences are increasingly instrumental in enabling and sustaining organizational intelligence.	Theory (Carayannis et al., 2017) Methodology
Meta-analysis is a common practice to analyze the disruptive, dynamic and complex environments.	An extensive literature review was used to develop the context of the paper, focusing on big data and organizational intelligence for enterprise excellence and resilience. In addition, a thematic literature review method was used to study the role and impacts of routines and artifacts in organizational change, policies, structure and performance.	

Qualitative thematic analysis

A qualitative thematic analysis is performed in the first step for meta-analysis. The purpose of this analysis is thematic identification of knowledge ecology management model. Thematic analysis is a method for identifying, analyzing and reporting patterns or themes within qualitative data. Therefore, thematic analysis turns the textual and various dispersed data into rich and accurate data (Braun, 2006). To this end, researchers have coded the topics used in the articles. Nvivo 10 was used for the programming process through which the main categories were identified and thematic matrix was developed. The keywords used (based on the main research questions) for searching scientific databases included: Knowledge Management in the Digital Business Ecosystem, Ecological Digital Business, Knowledge ecology management, Species of Knowledge, ecology management and scientific databases searched include: Academic Search Premier (EBSCO), Emerald, ProQuest, Sage Publications, Science Direct, IEEE, Google and Google Scholar search engines and SCOPUS.

According to Figure 2, 324 papers were selected after searching in scientific bases based on key words (identified based on the fundamental questions of the research). Then, 200 papers were deleted during the systematic study process. Finally, 106 papers met the necessary criteria for coding during the qualitative analysis stage. Then they were coded and the theme was formed. The main categories of the model are: digital business ecosystem (DBE), value-creating ecology (VCE) and social, mobile, analytical, cloud, IoT (SMACIT ecosystem). The relationship between the DBE categories and the SMACIT system was firstly tested by qualitative analysis with value-creating ecology (VCE). A matrix-coding query and the developed matrix cells are nodes that can be used to explore and further code on the data (Bergin, 2011).

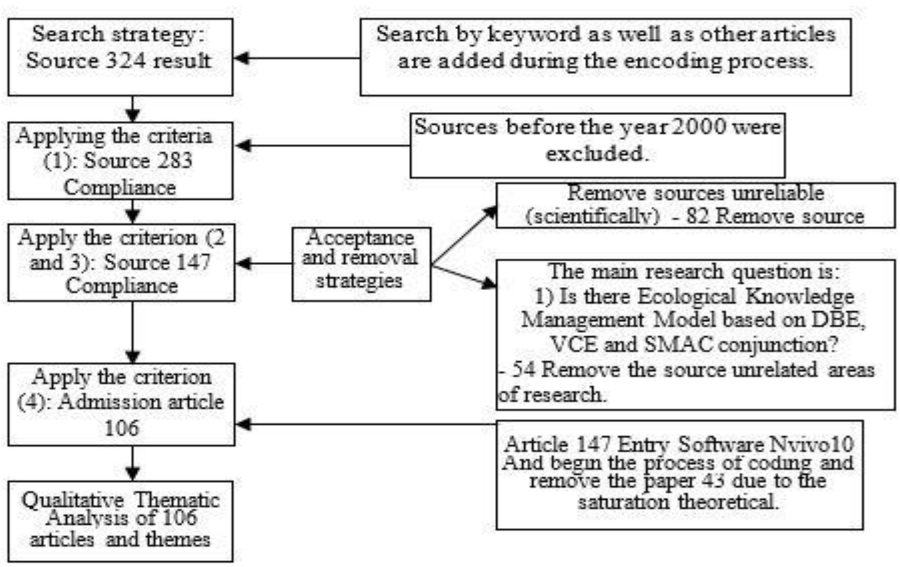

Figure 2: The steps of systematic review process

Matrix-coding query is a modeling used for illustrating relationship between two (main categories) categories in NVivo (Bazeley & Jackson, 2013). NVivo 10 software calculates the Pearson correlation coefficient based on the similarity of coding in the approaches studied (Wang & Yang, 2014). Table 2 shows the results of the correlation between the main categories of the model.

Table 2: Pearson correlation between main categories

	DBE	VCE	SMACIT
DBE		0.251264	
VCE			0.248734
SMACIT	0.142578		

Based on qualitative analytical results (Table 2), the relationship between the main approaches is confirmed. In addition, 25% correlation between the digital business ecosystem approach and the SMACIT ecosystem is due to value-creating ecology. Then, a 14 percent correlation was calculated between the digital business ecosystem and the SMACIT ecosystem. The whole theme of main categories (theme matrix) derived from the coded contents were listed in Table 3.

In NVivo software, the relationship between the themes of the main categories is run. This model confirms the relationship between DBE and VCE as well as the relationship between SMACIT and VCE (Fig. 3). The relationship between the code clusters and the research questions has been investigated using conceptual models in NVivo (Willis et al., 2016).

Table 3: The theme generated by coded contents

Digital Business Ecosystem (DBE)		Value-Creating Ecology (VCE)		SMACIT Ecosystem	
Categories	Themes	Categories	Themes	Categories	Themes
Business		Convergence Ecology		Social Ecosystem	
Keystone		Knowledge		social value co-creation	
Loosely coupled		Technology		Interactive web	
Quality		Industries		Sharing platform	
Negotiation		Co-evolution relationships		Knowledge Communities	
SMEs		Co-Design		Social Intelligence	
Co-Evolution		Customers		Mobile ecosystem	
Complex Evolving System		Coopetition Ecology		Functionality	
IOT		Accelerate R&D		Knowledge sharing	
Cross-industries		Alliance direct Competitors		Complex platform-based	
Peer-to-Peer (P2P)		Complementary Resourcing		Mobile Services	
Query-Cycle model		Co-opetitive Relationships		Inter-firm relations	
Community		Competitive Advantage		Analytical Ecosystem	
Socio-Technical Infrastructure		Diversified portfolio services/product		Business Intelligence (BI)	
Geographic		Lock-in		Intensive Computingsystem	
Regulatory		Reduces costs		Data lake (Big Data)	
Culture		Technological Innovations		Data Exploration	
Big-data		ICT Ecology drivers		Data Preparation	
Trust		Economic & Regulatory		Modeling/Scoring	
Engagement platforms (EPs)		Grow & Survive		Toolkit	
Ecology		Societal Preferences		Cloud Ecosystem	
Ecological Environment (EE)		Technological Evolution		Cloud Services	
Ecological Idea (EI)		Balance of Power		Cloud infrastructure provision	
Ecological Network (EN)		Knowledge ecology		Cloud characteristic	
Ecological relationships (ER)		Networked knowledge		Cloud-based Supply Chain IOT ecosystem	
Ecological strategy (ES)		Knowledge warehousing		IOT ecology Value Network	
Social-Ecological systems (ES)		Consumer Knowledge			

Ecological collaborative (ECO)	Cross-Industries Knowledge	internet-oriented (middleware) things oriented (sensors) semantic-oriented (knowledge) value co-creation and co-capture
Ecological Thinking (ET)	Social Networking knowledge	
ICT Ecology	Co-Create Ecology	
Industrial Ecology (IE)	Mass Customization	
Organizational Ecology (OE)	Actor-To-Actor (A2A)	
Ecological behavior	Ecosystem-to-Ecosystem	
Economy	Everyone-to- everyone (E2E) Economy	
Knowledge-based Economy	Co-Create social network	
Web2.0	Distributed value network	
Web 3.0		
Stakeholders centric		
Cyberspace data manipulate		
Multi-Agent systems(MASs)		
Mobile-Agent systems		
SOA		
Software Agent		
Population		
Co-Create Value		
Stakeholders		
Co-exist		
Dependent resources		
Topology		
ICT infrastructure		
Network		
Architectural shape Backend, Frontend systems ICT Outsourcing		

Since there was no possibility for the researcher to report all 106 papers (Table 3) for coding model categories; therefore, they were listed in Appendix A. Bazeley and Jackson (2013) argued that concepts do not 'emerge ‘from text. Rather, the researchers derive them as the process is not really automatic. Qualitative content analysis software, such as NVivo, is useful when 'a priori' model or set of factors exists. In other words, when there is an 'a priori 'model with which to 'code ‘up the data, researchers can use this set of factors in NVivo.

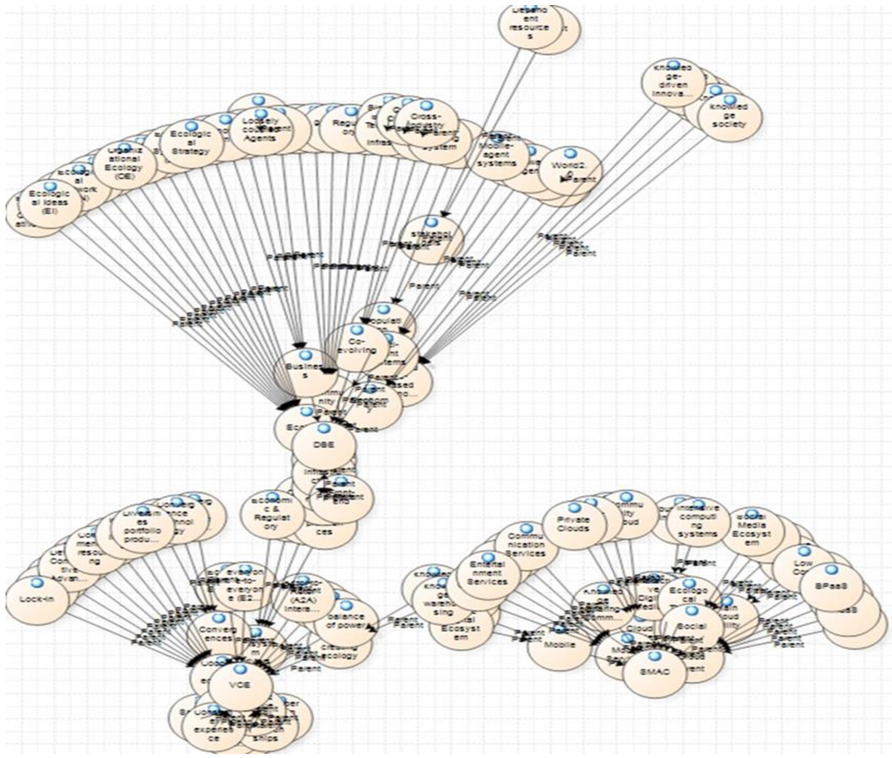

Figure 3: Conceptual model and interaction between the main categories and their themes

As previously mentioned, Briscoe (2010) and Graça and Camarinha-Matos (2017) outlined the components of the digital business ecosystem model. The main components of SMACIT are social computing ecosystems, mobile computing, analytical computing and cloud computing (Singh et al., 2016) and the IOT ecosystem. Hearn et al (2007) noted some of the main features of value creatiing ecology. These features were developed during the coding process.

QUANTITATIVE ANALYSIS

This section gives an explanation of how to use the quantitative method for validating the model. The prepared questionnaire contained 135 items. Each item represents each code in the qualitative analysis stage. The questionnaire was distributed among the experts of the knowledge-based companies operating in the field of information technology. The association of these companies with value-creating ecology and business ecosystems was the main reason for selecting knowledge-based companies (Kim et al., 2010). The questionnaire was designed with two objectives and distributed among the experts operating in knowledge based companies in the field of Information Technology. The first objective is quantitative analysis of the subject both based on the personal opinion of the researchers and the confirmation of the theme obtained by the experts. The second objective is to test the relationship between the digital business ecosystem and the SMACIT ecosystem with value-creating ecology and, consequently, the relationship of digital business ecosystems using the SMACIT ecosystem. Because of the novelty of the knowledge ecology management model presented in this paper, no basic knowledge companies are currently using this model. Therefore, this model is at the theoretical level and must be re-tested and verified after its implementation in companies (Sargent, 2013). It should be noted that, based on the coding of the main categories, the knowledge ecology management is considered the common factor of each of the three main management approaches of the model.

180 experts operating in knowledge-based enterprises in information technology were selected from the three provinces of Tehran, Isfahan and Qom, according to the official Iranian statistics site for Science and Technology Vice President. The Morgan table was used to select the sample size. Simple random sampling for sample selection was used based on Morgan's sampling table (Amirian et al., 2016). From the statistical population (n=180), a sample of 118 experts was selected based on the Morgan table. However, the researchers distributed 120 questionnaires to collect information among experts. The themes of the questionnaire were designed based on the main categories of the model.

The third generation software, referred to Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for modeling (Wong, 2013). Among these algorithms, the partial least squares (PLS) algorithm has become increasingly popular both in IS research and in other disciplines such as marketing (Albers 2010; Henseler et al. 2009) or strategic management (Hulland 1999). However, reminders of this approach's limitations have recently become more prominent. Consequently, researchers opt for a more careful application of PLS. Especially its statistical power at small sample sizes, the overall model fit, as well as the misspecification of measurement models have been the focus of recent discussions. (Urbach and Ahlemann, 2010). The main features of SMARTPLS 2.0 are the minimum sample size based on variance rather than covariance (Ringle et al., 2015).

Hypothesis

The output of the qualitative analysis showed the relationship between the main components of the model (Tables 2 & 3). Moreover, each of the main categories of the model reflects the knowledge ecology (Cheng and Leong, 2017, Del Chiappa and Baggio, 2015, Bhatiasevi and Dutot, 2014). That is, each of these three main categories has knowledge ecology. However, according to Briscoe (2010), it is important and essential to develop a distributed technical infrastructure for managing the knowledge of customers, SMEs and stakeholders in the digital business ecosystem. The SMACIT ecosystem provides a distributed technical infrastructure for extracting, storing, analyzing and scaling knowledge and, consequently, knowledge ecology management is realized.

Therefore, the main hypothesis of our research is as follow

H1: Knowledge Ecology Management Model is developed from the interaction of the business-ecosystem ecosystem including (business, coevolution, community, ecology, topology, population, economics, multi-factor systems), value creating ecology (cooperation and competition ecology, co-creation ecology, convergence of ecology, ICT Drivers, Information and Communication Technology, Co-Ecology), SMACIT Ecosystem (Cloud Computing, Mobile Computing, Social Computing, Analytics and (IOT) Ecosystem. Considering that PLS is routinely used for testing relationships derived from formal hypotheses (Rigdon, 2013), the following tests were used to confirm this hypothesis.

Model Measurement

Initially, the relationship between the main categories of the model was tested. Then, the SEM was utilized for modeling (Haenlein & Kaplan, 2004). The linear regression model provides a powerful device for organizing data analysis.

Researchers focus on the explanation of a dependent variable, Y, as a function of multiple independent variables, from X_i to X_K. Models are specified, variables are measured, and equations are estimated by ordinary least squares (OLS) (Menard, 2002). The main goal of linear regression is to fit a straight line through the data that predicts Y based on X. To estimate the intercept and slope regression parameters that determine this line, the least squares method is commonly used (Zou et al., 2003). Linear regression was used to test the proposed model and the relationships among the 19 themes identified in the qualitative analysis stage.

A significant level of 0.05 (sig <0.05) was considered for testing the linear regression among 19 main categories themes suggesting a linear relationship between model categories (Cohen et al., 2013). Cronbach's alpha test is widely used to measure reliability. This is because it is easier to use in comparison to other estimates (e.g. test-retest reliability estimates) as it only requires one test administration (Tavakol & Dennick, 2011). The Cronbach's Alpha questionnaire for this research has been calculated to be 0.863, which is acceptable (Bonett & Wright, 2015). The factor loading obtained in the export performance was higher than the recommended value of 0.7, showing a good individual reliability. Composite reliability, Cronbach's alpha, and communality exceed the threshold value (AVE>0.50, R, Square(R^2)>0.7, Cronbach's Alpha>0.7, and composite reliability>0,7) for internal consistency (Nunnally, 1978, Villena-Manzanares and Souto-Pérez, 2016) (Table 4).

Structural Model Measurement

What follows describes the goodness of the fit index. Table 4 shows that the construct validity is higher than 0.8. Therefore, the three main categories of model (DBE, VCE, SMACIT) have internal reliability.

Secondly, the values of the average variance extracted (AVE) being greater than 0.50 also confirms the existence of convergent validity. For convergent validity, researchers needs to examine the average variance extracted (AVE) (Blanco-Oliver et al., 2016). According to Henseler (2013), an AVE value of 0.50 and higher indicates a sufficient degree of convergent validity, meaning that the latent variable (constructs) explains more than half of its indicators variances (Henseler and Sarstedt, 2013). Measurement model is commonly used for Confirmatory Factor Analysis (CFA) and the researchers should obey the requirement needed to achieve the true model(Afthanorhan, 2013). Additionally, both the bootstrapping procedure with 5000 resamples (Henseler et al., 2014), and the percentile bootstrap 95% confidence interval (Vinzi et al., 2010) show the statistical significance of the path coefficients (Table 5).

In this model, DBE is exogenous construct and VCE and SMAC endogenous (Marin-Garcia and Bonavia, 2015). However, VCE is the most important endogenous model constructs. To confirm a hypothesis at 95% ($\alpha = 0.05$) and 99% ($\alpha = 0.01$) confidence level, respectively, minimum required T statistics is 1.96 and 2.58 (Gooshki et al., 2016). Likewise, according to Tenenhaus (2005), is The goodness-of-fit (GOF) 0.73 estimated (Tenenhaus et al., 2005).

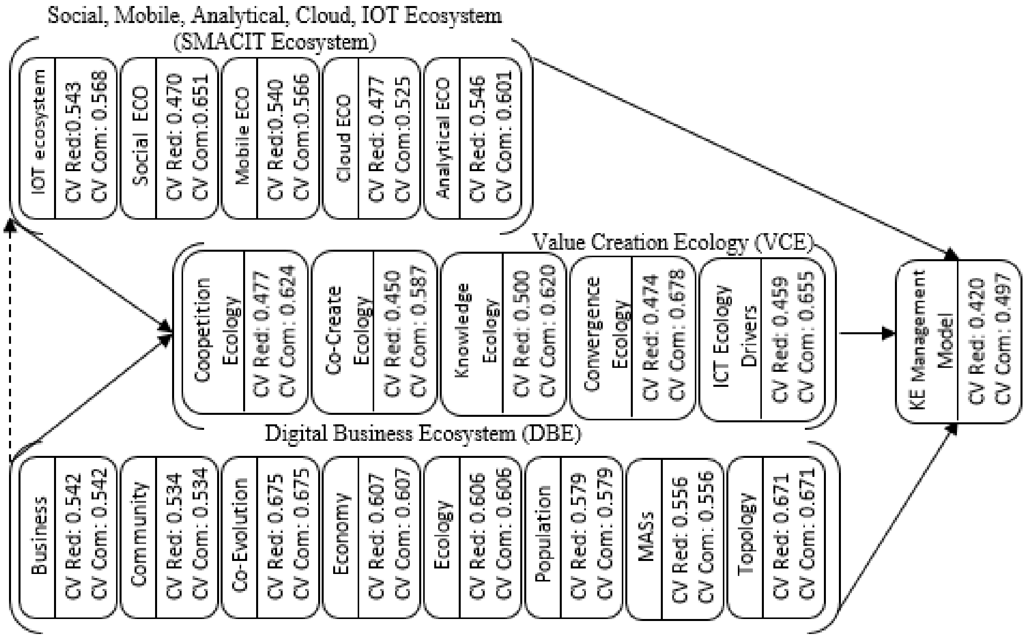

Figure 4: Knowledge ecology management (KEM) model

Table 4: PLS Quality Criteria

Categories	Themes	AVE	Composite Reliability	R Square	Cronbach Alpha
Digital Business Ecosystem (DBE)	Business	0.746168	0.936222		0.914639
	Community	0.685770	0.938480		0.923464
	Co-Evolution	0.705502	0.922875		0.895339
	Ecology	0.651685	0.953616		0.946401
	Economy	0.673375	0.948798		0.939149
	Multi-Agent systems	0.797079	0.921724		0.872305
	Population	0.779384	0.933873		0.905411
	Topology	0.705317	0.922790		0.895187
Value – Creating Ecology (VCE)	Co-Create Ecology	0.758276	0.956422	0.690771	0.946780
	Convergence Ecology	0.703697	0.904506	0.752671	0.858326
	Coopetition Ecology	0.670936	0.942178	0.780402	0.929740
	ICT driver Ecosystems	0.679761	0.894555	0.764670	0.842588
	Knowledge ecology	0.620052	0.954945	0.901947	0.948871
SMACIT	Social	0.684678	0.915532	0.772398	0.884292
	Mobile	0.697684	0.954015	0.880785	0.945656
	Analytic	0.784468	0.915812	0.789196	0.860328
	IOT	0.736105	0.900291	0.821907	0.872093
	Cloud	0.636505	0.960732	0.844014	0.955839
Model	Knowledge Ecology Management	0.511235	0.892540	0.852384	0.861672

Table 5: PLS analysis, paths and bootstrapping values

Exogenous →	Endogenous	Path Coefficient	Path T-Value	Standard Error (STERR)	Sample Mean (M)
Business	Cloud	0.270513	2.152526*	0.125673	0.276297
Business	Mobile	0.224206	2.141381*	0.090692	0.215738

Community	Convergence ecology	0.223938	2.030984*	0.110261	0.228444
Community	IOT	0.234356	2.211246*	0.109557	.227419
Ecology	Coopetition Ecology	0.705635	5.277516**	0.073523	0.709122
Ecology	Mobile	0.505565	4.744930**	0.112871	0.500104
Ecology	Social	0.482700	4.343831**	0.111123	0.484474
Economy	Cloud	0.444270	3.441057**	0.129109	0.442304
Economy	Knowledge Ecology	0.623052	5.936297**	0.056971	0.624867
Co-Evolution	Analytic	0.382961	3.580638**	0.106953	0.376259
Co-Evolution	ICT Ecology drivers	0.337872	3.224381**	0.104787	0.339820
Co-Evolution	IOT	0.541632	3.120644**	0.100108	0.530981
Multi-Agent System	Co-Create Ecology	0.214782	1.983621*	0.123182	0.209182
Multi-Agent System	Mobile	0.270827	3.579103**	0.075669	0.264302
Population	Convergence Ecology	0.291845	2.736479**	0.106650	0.288195
Topology	Cloud	0.261853	3.037786**	0.086199	0.259906
Topology	Co-Create Ecology	0.289020	2.060041*	0.140298	0.282630
Topology	Social	0.218355	2.129947*	0.093127	0.200166
Co-Create Ecology	Knowledge Ecology Management	0.251085	3.624154**	0.069281	0.252134
Convergence Ecology	Coopetition Ecology	0.203582	2.127638*	0.072184	0.190126
Coopetition Ecology	Knowledge Ecology Management	0.314513	4.959190**	0.063420	0.316953
Knowledge Ecology	Knowledge Ecology Management	0.432149	5.315448**	0.081301	0.430427
ICT Ecology drivers	Knowledge Ecology	0.381872	6.211062**	0.061483	0.381314
Social	Convergence Ecology	0.419351	3.702026**	0.113276	0.418425
Mobile	Analytic	0.544385	5.385063**	0.101092	0.540446
Analytic	Social	0.253929	2.204527*	0.115185	0.251690
Cloud	Co-Create Ecology	0.386197	3.064237**	0.126034	0.397308
Cloud	ICT Ecology drivers	0.581794	5.477366**	0.106218	0.580176
IOT	Cloud	0.495387	2.693123**	0.115630	0.479987
IOT	Analytical	0.598431	3.107529**	0.098169	0.580945
IOT	Coopetition Ecology	0.399478	3.079574**	0.113019	0.381112

PLS path models are formally defined by two sets of linear equations: the inner model and the outer model. The inner model specifies the relations between unobserved or latent variables, while the outer model specifies the relations between a latent variable and its observed indicators or manifest variables (Henseler and Sarstedt, 2013). Inner model is shown in Table 4. The relations between a latent variable and its observed indicators is higher all the coefficients (load factor) than 0.7 (Khrouf and Frikha, 2016). In this article, all coefficients were estimated factor greater than 0.8.

This test's application follows a "blindfolding" process that enables the construction of Q2 indicator (1-SSE/SSO). The interpretation of this value take 0 as a reference level. In this way, the model has a predictive value when the indicator is positive (Pérez-Valls et al., 2017). The results derived from the analysis of the model present a Q2 indicator's value for the endogenous variable. The blindfolding cross-validation indices (CV-Redundancy and CV-Communality) (Vinzi et al., 2010), is shown in the figure 4.

DISCUSSION AND FINDINGS

Unfortunately, due to the novelty of the Knowledge Ecology Management Model presented in this paper, no knowledge – based companies are currently using this model. According to the path coefficients in Table 5, all t-values are larger than 1.96 and according to Table 4 (AVE> 0.5), a significant relationship is confirmed between the main categories of knowledge ecology management model. Additionally, the positive cross-validation of linear model quality shows the quality of the knowledge management ecology model by linking the main categories. Therefore, the null hypothesis is rejected and the H1 hypothesis is verified. The goodness of the fit index is also estimated at 0.73. The Composite Reliability and the Cronbach Alpha for each category are greater than 0.7 (Table 4); therefore, the coding accuracy is verified by experts.

Briscoe (2010) maintains that "the digital business ecosystem is a combination of digital ecosystems, community and business," but he has not presented any explanation for how these ecosystems are combined together. Meanwhile, according to Briscoe, the integration of Wikipedia and Arxiv.org could lead to the creation of a digital knowledge ecosystem, if there is a distributed technical infrastructure. This paper presents a distributed technical infrastructure using the SMACIT ecosystem. As Briscoe has pointed out, topology is a distributed technical infrastructure. Therefore, in accordance with Fig. 4, the topology presented in this paper is related to the cloud ecosystem. There is a strong integration between the components of the SMACIT ecosystem, which means that the SMACIT ecosystem leads to a distributed technical infrastructure and ultimately knowledge ecology management. Based on the above descriptions, the value creating ecology has been used to display the relationship between DBE and the SMACIT ecosystem.

Chan (2015) also demonstrates that because of the nature of the IOC ecosystem in which companies need to collaborate with existing competitors and companies in different areas, it's easy to see why the old business models are not suitable for modern enterprises." As noted earlier, the relationships with competitors imply "co-operation ecology and coopetition ecology." Therefore, one of the main questions in the questionnaire asked from the experts of knowledge-based companies was the existence of the correlation between the IOT ecosystem and the coopetition ecology. The existence of the relationship between the two components has been confirmed based on the respondents (Table 5).

CONCLUSION

The knowledge ecology management model is at the theoretical level and should be tested and approved after implementation in the companies. However, the effectiveness of the knowledge ecology management model is confirmed by the results of a survey of experts. The results of this research can be categorized into two types. One is related to test the main hypothesis of the research and the other benefits derived from the interaction of the three approaches to the management of the digital ecosystem and value creating ecology and the SMACIT ecosystem. As mentioned earlier, there are more than one issues affecting the creation of knowledge ecology in ecosystem systems (Tàbara & Chabay, 2013). People and their relationships are an inseparable part of the research model components. Therefore, the knowledge ecology model was derived from the interaction of all components of the proposed model (Table 3). Because of the prevalence of mobile apps, cloud computing, analysis and social media are accessible to all users through mobile apps (Chen et al., 2012). All components of the knowledge ecology management model include business, coevolution, population, community, economics, multi-factor systems, ecology, topology, convergence ecology, ecology of cooperation and competition, knowledge ecology, co-ecology, ICT driving force, Cloud computing, analytics, mobile, community, and IOC ecosystems contribute to the development and sharing of knowledge leading to the formation of knowledge ecology management (Figure 3). To conclude, we can say that knowledge ecology management was developed from the interaction of the digital business ecosystem mediated by the SMACIT ecosystem; however, this interaction is not realized through the value chain or supply chain, but the value creating ecology in closed-loop and network relationships.

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