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Inter-rationality; Modeling of bounded rationality in open innovation dynamics

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ABSTRACT

If any firm or agent makes decisions under inter-rationality, which is a kind of bounded rationality in open innovation dynamics, it would not stop growing at a certain point of the reverse-U curve, but grow continuously following a zigzag pattern. In this study, we examine whether there is any relation between open innovation and sustainable economic growth, which might explain why some firms grow continuously and others collapse. A conceptual and mathematical model of inter-rationality in open innovation dynamics is constructed. The theoretical contribution of inter-rationality that it could be the precondition or essence of economics, political economics, social science, or open innovation engineering in the digital transformation era as the economic human's dominant type of bounded rationality. The zigzag growth pattern resulting from open innovation dynamics which is based on the inter-rationality of economic agents could suggest any practical way to overcome the growth limits of firms or economic system.

1. Introduction

In the modern capitalist system, neoclassical rationality is a baseline assumption for models of economic behavior. Nonetheless, important scholars of the past argued that the capitalist economy is neither rational, nor is it ever in equilibrium, given the dynamic rate of change of economic activity (Marx, 2004; Schumpeter, 1934, 1939; Simon, 1997). To reflect capitalism's non-equilibrium characteristics, Simon (1997) developed the concept of bounded rationality about economic behavior, which relaxes the assumption of neoclassical rationality with the idea that economic agents know all information, and consider it all while making economic choices. Another important dynamic influence on the economy is open innovation, defined as innovation beyond the boundary of a firm, sector, region, or innovation system and is fast becoming a dominant paradigm (Chesbrough, 2003). Currently, with the start of the fourth industrial revolution, open innovation dynamics are becoming the new normal in capitalist economies (Lee et al., 2018; Yun et al., 2018). Understanding the dynamics of open innovation is relevant not only to firms but also for the whole economic system (Witt, 2017; Yun, 2015).

In this study, we investigate the following questions: *Is there any relation between open innovation and sustainable economic growth? Why do some firms grow continuously and others stop growing or collapse?* These research questions are addressed by developing a conceptual and mathematical model of open innovation under inter-rationality, which addresses the economic selection processes of individuals, firms, and artificial intelligence (AI) in open innovation systems. In the appearance of digital transformation which motivates digitally modified business, diverse artificial intelligence such as intelligent robot, autonomous cars, or vacuum intelligent cleaner could be the agent in the actor-network theory (ANT) (Callon and Blackwell, 2007; Westerman et al., 2014). Specially with the expansion of ANT in open innovation paradigm, any AI could be the agent which is required to succeed in a sustainable innovation development process (Aka, 2019; Choi et al., 2018; Murdoch, 1998; Tanev et al., 2015).

In fact, there exist research gaps 1) between the economic condition, and open innovation strategy, and 2) between economic effects and open innovation results. The study is targeting 2 research gap issues like 1) the economic condition of open innovation, in other words, the inter-rationality, and 2) the growth pattern of economy or firm under open innovation dynamics. Finally, this research focuses on the economic effect of open innovation in the aspects of sustainable development of firm, or the sustainable growth of economy by closing the research gap between economics and open innovation research.

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To answer these questions, a conceptual model of rationality in open innovation dynamics is developed based on an in-depth literature review. This concept is then expanded upon by conducting mathematical modeling of the rationality of open innovation dynamics. This is referred to as the inter-rationality model, which can be applied when any firm or agent makes an economic decision. Second, we validate the inter-rationality model logically by applying causal loop model building and conceptual experiments. Additional literature and case studies of open innovation are considered to inform this investigation. Causal loop modeling shows that the concept of inter-rationality adds value in terms of understanding open innovation dynamics. Third, we validate the inter-rationality model by simulating open innovation dynamics with an agent-based model (ABM). The ABM simulation results further enhance the understanding of open innovation dynamics by leveraging the inter-rationality concept. Fourth, we discuss the value of the inter-rationality concept in an open innovation paradigm-based economy. Again, this is achieved by developing conceptual experiments and reviewing additional, related strains of research.

2. Literature review

2.1. Open innovation

Acquiring and selling knowledge through markets for ideas (MFIs) is growing trend for organizations embracing the open innovation paradigm such as 1) open and external market like InnoCentive, 2) closed and external market like YourEncore, 3) open and internal market like connect and develop portal, or 4) closed and internal market like SolutionXchange (Garavelli et al., 2013). Markets for ideas which are virtual marketplaces connecting knowledge owners, and knowledge seekers, could find its root in the open innovation paradigm, and empirical data clearly demonstrate how its economic importance is constantly growing (Natalicchio et al., 2014). In the same context, crowdsourcing initiatives are increasingly spreading among organizations opening up their internal innovation processes to the inflow of external knowledge (Natalicchio et al., 2017).

By the way, though the creation of innovations often requires firms to be open, but the commercialization of innovations typically requires firms to be closed off and protect their intellectual property (Laursen and Salter, 2014). The paradox of open innovation, whereby innovative performance is defined by an inverted U-curve, is often referred to in this context (Laursen and Salter, 2006). A project level analysis in the German market also revealed the inverted U-shaped relationships between collaboration breadth and radical innovation performance, as well as collaboration depth and incremental innovation performance (Kobarg et al., 2019). In a similar analysis of innovation alliances, innovation performance is found to follow a parabolic, inverted-U-shaped function of technological cognitive distance between the alliance partners (Nooteboom et al., 2007). In fact, as the cooperation by open innovation can benefit hurt firms at the same time, absorptive capacity of firm maximizes their learning capability at an intermediate knowledge distance with reverse U curve because the too close condition with lock-in remains nothing to learn, and the too far condition with misunderstanding is too difficult to learn (Egbetokun and Savin, 2015). So to say, partner selection of firms is driven by absorptive capacity which is itself influenced from cognitive distance and research and development (R&D) investment allocation, and innovation networks among firms exhibit small world properties which are generally robust to changes in the knowledge regime with the emergence of tacit knowledge (Savin and Egbetokun, 2016). In fact, the coevolution of endogenous knowledge networks and knowledge creation as a result of open innovation could occurs under diverse conditions in the collaboration for knowledge creation, the role of previous knowledge, the process of partner selection, or the structural disparities on knowledge diffusion in networks (Mueller et al., 2017; Tur and Azagra-Caro, 2018).

Small and medium-sized enterprises (SMEs) that pursue open innovation for market-related motives, such as meeting customer demands, or keeping up with competitors, also face many important challenges related to organizational and cultural issues. They are likely to be more dependent on external contacts, which means the inverted-U curve of the innovative performance of open innovation applies to SMEs as well (van de Vrande et al., 2009). Hence, open innovation does not automatically enhance innovative performance. To achieve strong open innovation performance, changing business processes to enable innovation generation, dissemination, and absorption in a harmonious way is pre-requisite (Chesbrough, 2019).

Even though there is an upper bound on altruism, applying the concept of bounded rationality can account for the evolutionary success of genuinely altruistic behavior, and this may also explain open innovation actions (Grant, 2013; Simon, 1990). Additionally, the concept of shared value, which focuses on identifying and expanding the connections between societal and economic progress, is a form of altruism, which may help societies absorb innovations, including by enabling open innovation (Chesbrough, 2019; Porter and Kramer, 2019).

To summarize, it can be said that the foundations of sustainable enterprise performance can be obtained through collaboration with other enterprises, entities, and institutions. The dynamic capability of open innovation can be achieved so long as threats are managed by a dynamic capabilities framework as a way to better understand the strategic management of open innovation, which can then help to better explain both success and failure in open innovation (Bogers et al., 2019; Teece, 2007). Open innovation dynamics depend on the organization's desire to either foster greater growth (which favors a more open strategy when there are few legacy customers and many new arrivals), or secure greater control and profit directly from the innovation (which favors a more proprietary strategy when there are few customers to attract with an open strategy) (Appleyard and Chesbrough, 2017).

With the growing recognition of the value of open innovation in firms, the labor market is increasingly rewarding social skills that reduce coordination costs, allowing workers to specialize and work together more efficiently (Deming, 2017). For many companies, a unique and sustainable competitive advantage comes from engaging in open innovation more effectively than competitors, thereby attracting key resources to create cooperative networks (Moore, 1993).

2.2. Bounded rationality of economic agents

Human decisions are often sub-optimal, whereby they are seemingly irrational, show compromise effects, or are affected by biased probability estimates, and this is encapsulated by the concept of bounded rationality (Lorkowski and Kreinovich, 2018). Simon (1972) defined bounded rationality, stating that “the capacity of the human mind for formulating and solving complexity problems is very small compared to the size of problems solutions are required for objectively rational behavior in the real world or even for a reasonable approximation to such objective rationality.” Bounded rationality is said to explain a plethora of economic events, such as the constant fluctuation of bar attendance or the price of bonds (Arthur, 1994).

Relying on the concept of bounded rationality, rather than neoclassical rationality, has enabled a more general consideration of problems in the assumptions of rationality, particularly for problems of subjective understanding, perception, conflict of interest, and less intentional conceptions of the causal determinants of action (March, 1978). In fact, human agents often deviate from neoclassical rationality in practice, because they are limited by bounded rationality that constrains them. For difficult decisions, using rough-and-ready judgmental heuristics can be faster and more frugal, and this generates biased judgments and decisions (Agosto, 2002; Colman et al., 2008).

The concept of bounded rationality can also be applied to organizational learning, which is part of firms' innovation processes considered in case studies of organizational learning (Simon, 1991). The limits of rationality observed on behalf of firms could result from diverse factors such as risk and uncertainty, incomplete information about alternatives, or complexity, and these factors are present in open innovation situations (Lee et al., 2018; Simon, 1972). The bounded rationality principle is a basis for the construction of organizational behavior theory because it is concerned with identifying and studying the limits to the achievement of goals that are, in fact, the limitations on flexibility and adaptability of individual goal pursing (Simon, 1979). According to the principle of bounded rationality, an organization's performance and success are governed primarily by the psychological limitations of its members, such as the amount of information they can acquire and retain and their abilities to process it in a meaningful way (Morecroft, 1983). The general features of selective searches of bounded rationality are 1) failure to know all the alternatives, 2) satisficing as a result of uncertainty about relevant exogenous events, and 3) inability to calculate consequences (Simon, 1979). All these ideas have been taken as the starting points for a number of attempts to build theories of the firm incorporating behavioral assumptions (Simon, 1979).

As economic analysis acquires a broader concern with the dynamics of choice under uncertainty, procedural rationality will become increasingly important as well as research on AI and cognitive psychology (Simon, 1978, 1986). Meanwhile, AI techniques that are based on bounded rationality have been developed for a variety of decision-making scenarios (Marwala, 2014).

2.3. The limits of growth in the economy

The economy in the United States (US) grew sharply from 1870 to 1970 (Gordon, 2017). This included the particularly successful period between 1940 and 1970, which was spurred by social reforms such as limiting labor working hours per week to 40 h and regulating monopolies, and by technological innovations (Gordon, 2017). However, after the 1970s, the US economy's growth rate declined and stagnated (Gordon, 2017). In sync with the wealth gap between the top 1 % of US citizens and the other 99 % becoming exaggerated at the end of the 20th century, the US economic growth rate was approaching 0 % (Stiglitz, 2015a). In other words, the price of inequality is the main factor that affects the decline of US economic growth (Stiglitz, 2012). Stiglitz has proposed new rules for the American economy, with an agenda for growth and shared prosperity, which address the basic mechanisms of capital accumulation to end poverty (Sachs, 2006; Stiglitz, 2015b).

Economists have proposed theories about the limits of growth (Banerjee and Duflo, 2019; Solow, 1956). Alternative theories consider that growth rates can increase over time, and the effects of small disturbances can be amplified by the actions of private agents with creative destruction (Aghion and Howitt, 1990; Romer, 1986, 1994). Namely, researches on how to stimulate economic growth have been considered: 1) tax cuts for the less wealthy 90 %, stimulating the upper 10 % to challenge the startups and increase employment; 2) cities as the new growth escalator; and 3) certain structures such as feedback loop among market open innovation, closed open innovation, and social open innovation. These will motivate economic growth such as that in the US in the 1950–80s, India in the 21st century, or South Korea in the 1970–90s (Acemoglu et al., 2001; Lee et al., 2018; Moretti, 2014; Zidar, 2019).

3. Conceptual model of inter-rationality in open innovation dynamics

3.1. Bounded rationality in open innovation dynamics

This conceptual step can be the best explained by using an example. We assume that there are two rooms with completely different conditions, which will both be cleaned by the same type of bounded rationality-based AI vacuum cleaner (Fig. 1). If the AI cleaning machine is used in room (A), which is a circular room that has a lot of micro dust, the machine can learn based on the bounded information range that it experienced to clean that type of room. If the same vacuum cleaner that was accustomed to room (A) is then applied to room B, the required cleaning ability for room (B) will be out of scope.

The example of the bounded rationality of the AI cleaning machine, whereby experience dictates capability, is similar to the bounded rationality of humans as economic agents. Bounded rationality of economic agents leads to the diversity in the growth of firms and the economic system.

Neoclassical rationality will propose the best rational model of AI vacuum cleaner which can be applied to these two rooms, and it will not interact with the opposite agent in several aspects such as room structure, and characteristics of trash. But the inter-rationality model

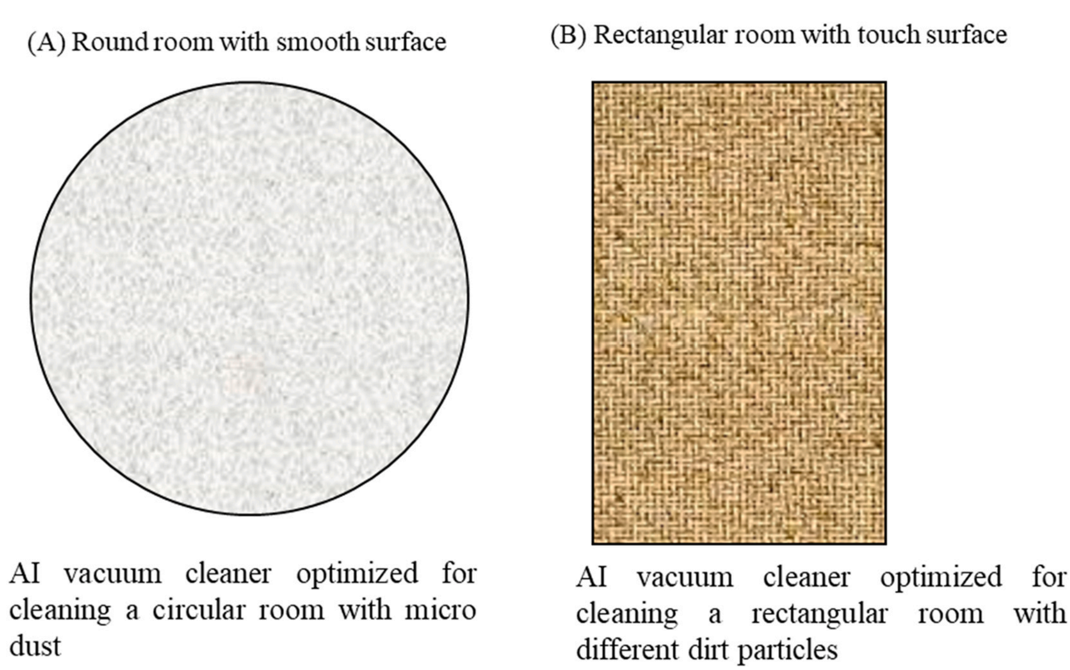

Fig. 1. Bounded rationality in open innovation dynamics – the example of an artificial intelligence (AI) vacuum cleaner.

proposes not the maximum functioning AI vacuum cleaner but individually emergent AI vacuum cleaner in each room which is combined by interaction with the opposite agents such as room or trash here.

3.2. Appearance of inter-rationality as bounded rationality

Classical and neoclassical economics assumes 1) human goals and motivations can be defined in the form of a utility function, which leads an individual to make consistent choices among all possible bundles of goods and services and 2) economic actors always choose the alternative that yields the greatest utility among all alternatives (Schwartz and Simon, 2002; Simon, 1966). These assumptions are reflected in the general rationality space, which is most significant under closed innovation conditions (Fig. 2). The small portion of bounded rationality in Fig. 2 solely reflects the incompleteness of information available to economic agents.

In an open innovation context, actors do not know all the alternatives available. They might have only incomplete and uncertain knowledge about the environmental variables that will determine their choices' consequences. In this context, they are unable to make the computations required to identify an optimal choice (Simon, 1993). Bounded rationality is used to designate rational choices that consider the decision maker's cognitive limitations, which may be based in either knowledge or computational capacity in the open innovation scenario (Simon et al., 1987).

Bounded rationality better accounts for “diversity” among economic actors than the neoclassical rationality assumption does, which is particularly relevant in the open innovation context (Egidi et al., 1992; Lee et al., 2018). Building on the concept of bounded rationality, inter-rationality considers “docility” of individuals when interacting with others. The “docility” here is based on the idea of Simon who used “docility” as the tendency to reflect on others' suggestions, recommendations, persuasion, and information obtained through social channels as a major basis for making choices (Simon, 1993).

3.3. Inter-rationality as a form of bounded rationality in open innovation

A rational behavior theory has been concerned with the rationality of individuals or organizations even though the two are not wholly distinct (Simon, 1972). In this paper, both are considered as inter-rational agents. Additionally, AI agents can be treated as inter-rationality agents when considered in the open innovation context. Inter-rationality is a form of bounded rationality in open innovation dynamics in the situation that inter-rationality portion in bounded rationality is increasing (Fig. 2). Bounded rationality in open innovation dynamics could not be explained by traditional bounded rationality logics such as the limits of human cognition, the lack of information or time, or the non-balance in information between economic agents. Inter-rationality focuses on the complexity or risk which is motivated by the interactions among agents in addition to the emergence which is triggered by the interactions among economic agents, or new combination among technology, market, organization and etc. which are over the boundary of economic agents.

Inter-rationality has three conditions (Fig. 3). The first condition reflects when an economic agent knows all the information within their boundary, which aligns with the neoclassical rationality concept. The second condition applies when an economic agent does not know all the information within this boundary, which reflects the bounded rationality concept. The third condition reflects that the sum of economic agents in the system equates to something more than the simple sum of component agents because they are interconnected and create open innovation (Meadows, 2008). An economic agent under the first condition is superior to others because they know more; the preference curve is persistent. They can also decide according to the assumption of neoclassical rationality.

Under the second condition, no candidate is superior because no persistent preference curve exists that can be used to select among the agents. Applying this logic to the context of open innovation, this means agents who join open innovation networks and have their own special characteristics would produce emergencies when they try to make new combinations with other agents (Chesbrough, 2006; Lee et al., 2018; Schumpeter, 1939). Thus, it is logically impossible to select an agent who is better in all aspects under the open innovation philosophy.

Applying the third condition to open innovation, it can be concluded that the sum of inter-rational agents leads to the emergence of innovations, which do not belong to a certain agent as a result of convergence, fusion, new connections, or new combinations (Broring, 2010; Kodama, 1992; Lee, 2015). Even though individual firms are faced with the inverted-U curve in open innovation, firms in the system will continuously pursue open innovation based on their expectations of an overall positive performance. Consequently, there will be an additional surplus value by interconnection between agents, which is not attributable to a certain agent and can be generated in the inter-rationality system.

Condition 1st could be defended from the bounded “rational” model, or neoclassical rational model enough (Berg and Gigerenzer, 2010; Simon, 1972, 1993, 1995). Condition 2nd could be deducted from several materials on “bounded” rational model which have origins from the limits of human cognitions, imperfect information, non-balance of information, or not enough resources etc. (Dequech, 2001; Meadows, 2008; Simon, 1993). Condition 3rd is logically directly from the new combination, and open innovation which motivates emergences

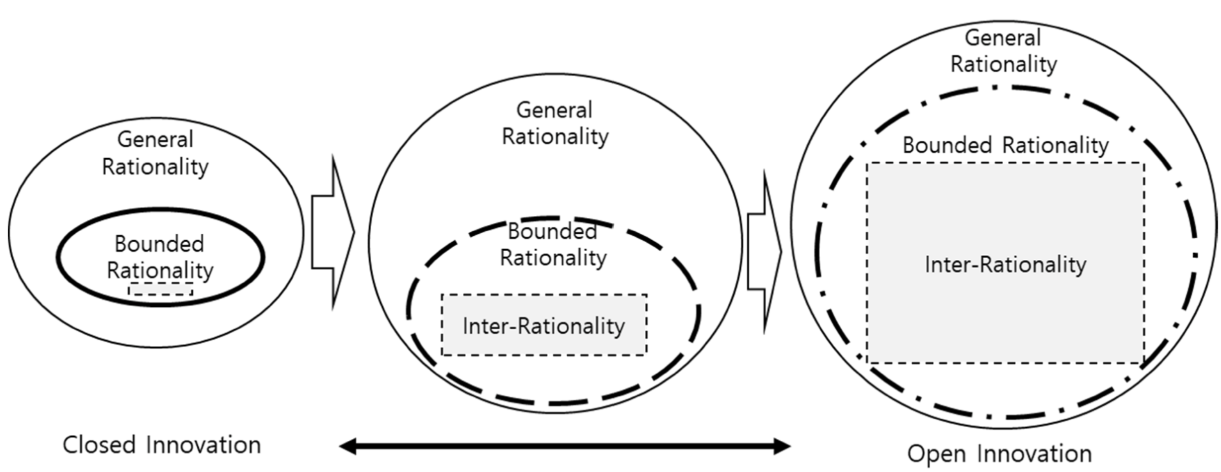

Fig. 2. Evolution of inter-rationality with the expansion of the open innovation paradigm.

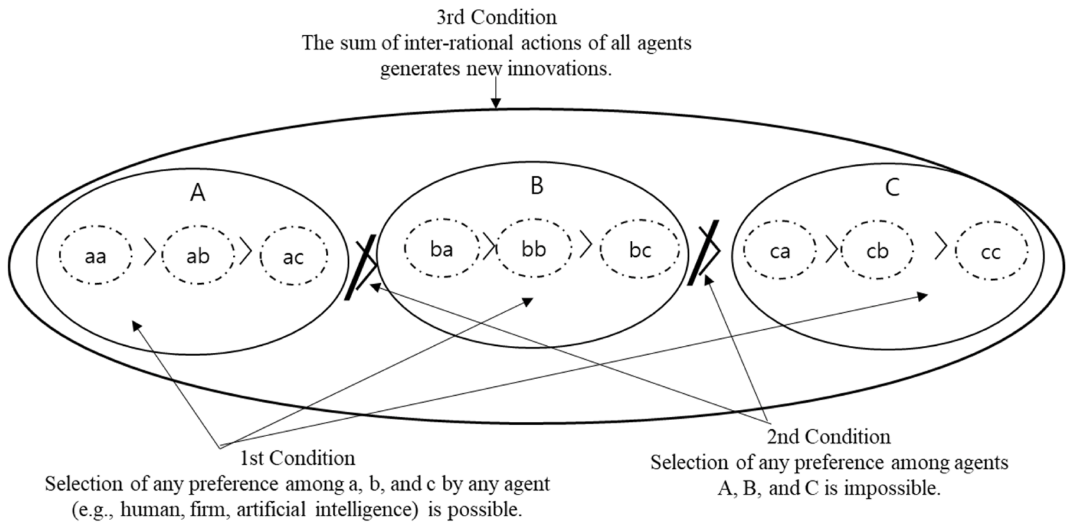

Fig. 3. Concept model of inter-rationality in an open innovation context.

(Chesbrough, 2003, 2006; Schumpeter, 1939).

4. Mathematical understanding of inter-rationality

4.1. Mathematical modeling of bounded rationality

The classical view of rationality is that decision-making is a fully rational process of finding an optimal choice among available alternatives. Simon's (1976, 1990, 1997) concept of bounded rationality is based on the following points of criticism as neoclassical economics does not explain 1) the origin of alternatives, 2) the content of the utility function, 3) how items are placed on the agenda for decisions, and 4) how the economic actor connects alternatives with their consequences (measured in terms of utility), that is, it does not sufficiently explain the computational means.

Under bounded rationality, decision-makers act as satisfiers, which means alternatives are searched until a satisfactory alternative is found. Further, bounded rationality considers the implications of the existence of goals, of agents' search for improvement, and of long-run success (Radner, 1973; Shiller et al., 2008).

4.2. Definition of inter-rationality

The definition of inter-rationality is following the definition of bounded rationality by Simon, and is deterred from the extension of the bounded rationality to interaction because the fitness of human beings in evolutionary competition is defendant of suggestions, recommendations, persuasion, and information obtained through social channels (Simon, 1993).

(a) Each individual exhibit bounded rationality (Simon, 1972, 1979, 1991).
(b) Each individual has their own preference criteria for their decision processes, and individual preferences are incomparable.
(c) There is a unique rationality convergence point that emerges from the interaction among individuals.

4.3. The growth of system knowledge

In this section, we study how the system performance grows under the circumstance of inter-rationality.

Let I be an index set of individuals. For each individual $i \in I$, we denote the open innovative performance of the individual i as K_i and assume that K_i depends on the open innovation depth, t (also known as the intensity of inter-rationality; Laursen and Salter, 2006), and the open innovation breadth, J (also known as the degree of open innovation; Laursen and Salter, 2006) (Table 1). Here, for each $i \in I$, we use the multi-index $J = \{j_1, j_2, \ldots, j_k\} \subset I$ in the case that an individual i interacts with individuals $j_1, j_2, \ldots, j_k \in I$. Further, to quantify the open innovation breadth, we adapt the symbol $|J|$, where $|J|$ stands for the size of the set J. Using this notation, by $K_i(t, J)$, we mean the open innovation performance of the individual at the given open innovation depth t, and the open innovation breadth J. Also, $K_J(t. L)$ refers to the total open innovation performance of the system of all individuals $j_1, j_2, \ldots, j_k \in I$, for a given depth t, and breadth $L \subset I$. We assume that the performance function K_i of the individual i is proportional to individual i's knowledge and an i's knowledge is directly proportional to the rationality of individual i.

The following weak axiom of the open innovation performance under the inter-rationality circumstance is assumed, according to the literature on open innovation:

(1) For every $i \in I$, $K_i(t, J)$, is the inverted-U curve for a fixed t as the size of the open innovation breadth J increases (Fig. 4). Following the concept of bounded rationality, as defined in (a), each individual i knows when to stop expanding the breadth of their open innovation when K_i decreases.
(2) For every $i \in I$, $K_i(t, J)$, is also an inverted-U curve for a fixed J as the open innovation depth, t, increases (Fig. 4). Following the concept of bounded rationality, as defined in (a), each individual i knows when to limit the open innovation depth, when K_i decreases.

4.4. Zigzag pattern of economic growth; theorem and cases

As discussed, we can prove the following theorem, which explains how the total innovative performance increases continually when the open innovation in the system progresses and inter-rationality is

Table 1
Symbols and their meanings for zigzag growth theorem.

Symbols	Meanings
I	An index set of individuals
i, j, l	Elements of I
t	Open innovation depth variable
J, L	Open innovation breadth variables and $J, L \subset I$
$K_i(t, J)$,	Open innovation performance function of $i \in I$ at (t, J)
$\|J\|$	The size of the set J

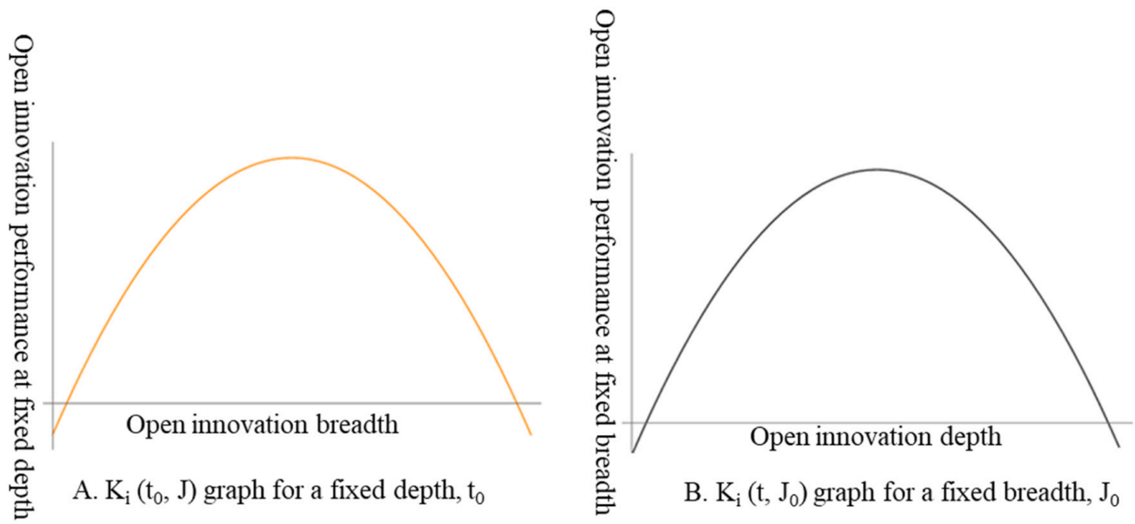

Fig. 4. A, K_i (t_0, J) graph for a fixed depth, t_0; B, K_i (t, J_0) graph for a fixed breadth, J_0.

widespread.

Zigzag Growth Theorem: The total innovation performance $K(t,J)$ of the system of the individual set I constantly increases along a zigzag course under the circumstances of inter-rationality. In other words, as t and $|J|$ are simultaneously increasing, so does innovation performance.

Proof. At a given depth t, and a fixed open innovation breadth J, there are diverse individual performances, $K_{j_\alpha}(t,J)$ for $j_\alpha \in J$, $\alpha = 1, 2, \ldots, k$. Following definition point (b) of the inter-rationality concept, we cannot compare K_{j_α} with each other. Every individual j_α has their own, incomparable rationality. Nevertheless, as the depth t (or equivalently, the intensity of the inter-rationality) increases among the individual j_α's, we have the converged level of rationality results by (c) of the definition of inter-nationality. In terms of the innovation performance, we denote this as K_J (Fig. 5). Because of the inverted U-shaped property of K_J (Fig. 4) and because of the above weak axiom (2) (or the bounded rationality assumption), the converged performance K_J is stopped at time t_1 and assumes a zigzag path to move in the direction of the open innovation level L (it turns to the left in Fig. 5). Next, a slightly higher level $L = \{l_1, l_2, \ldots, l_k\} \subset I$ of the open innovation breadth can be considered. More precisely, the open innovation breadth L contains the index J as a subset, and, hence, we have $|J \cap L| \approx |J|$and $|J| < |L|$. In this case, at time t_1, we have

$$K_i\,(t_1, J) < K_i\,(t_1, L) = K_J\,(t_1, L).$$

Note that i is contained in J and L. In fact, we have applied the property of bounded rationality and inter-rationality at local t_1. This implies that the performance at a slightly higher level of L is slightly superior to the performance at level J. Additionally, note that at time t_1, individual i's performance $K_i(t_1,\cdot)$ has already converged to $K_J(t_1,\cdot)$. The open innovation breadth curve has also the inverted U-shaped form as L

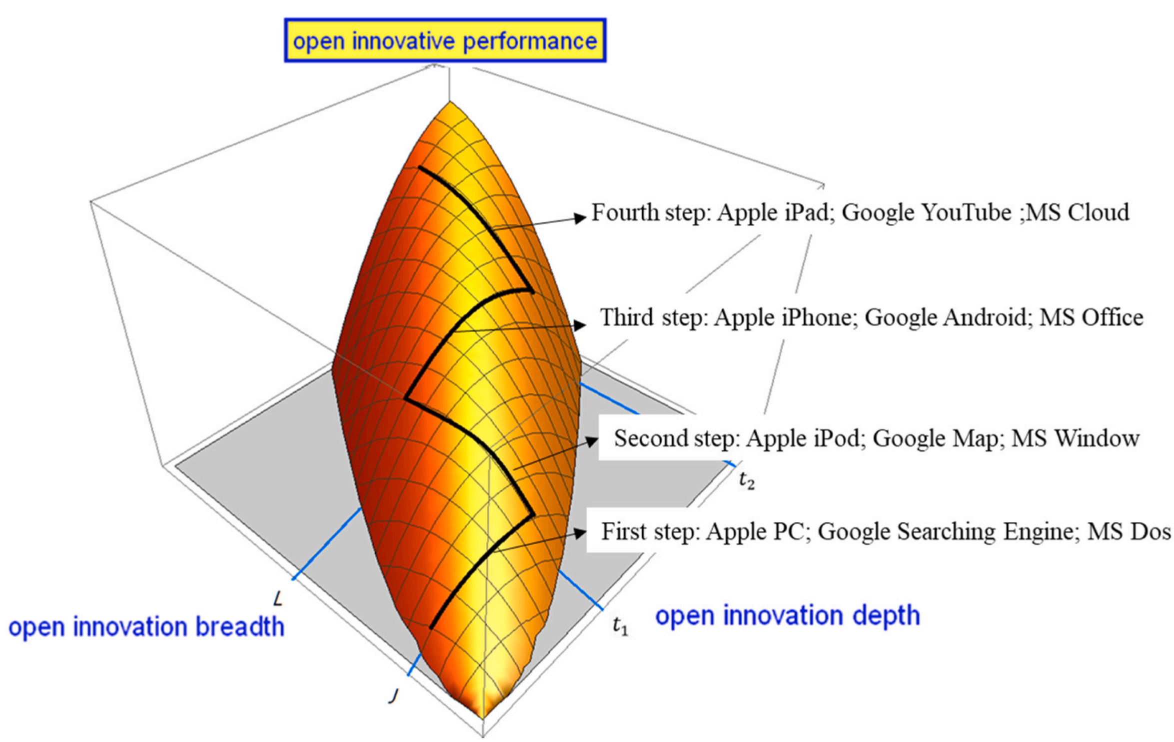

Fig. 5. Zigzag pattern of performance improvement when agents are inter-rational in the context of open innovation.

increases. By the weak axiom (2), $K_J(t_1,\cdot)$ stops at some open breadth, say it L, and finally, $K_J(t_1,L)$ zigzags (it turns to the right in Fig. 5) in the direction of the time progression. Repeating the same zigzagged argument, because of the inter-rationality property and the above weak axioms (1) and (2), $K_J(t_1,L)$ stops at time $t_2 > t_1$ and it converges to $K_L(t_2,\cdot)$. At each zigzag step, the performance function $K_J(t,L)$ is bigger than that of just before step, because of the weak axiom (1) and (2). These arguments complete the proof of the Zigzag Growth Theorem.

Hence, by this kind of zigzagging, we can find an example in Apple, where there was zig step personal compute r(PC), zag step iTunes, second zig step iPhone, and second zag step iPad (Fig. 5). This is the ascending property of the performance, and the fact that the open innovation level in breadth and depth constantly increases, the converged knowledge K_L of the system, or open innovation performance, constantly increases.

Most of firms which are sustaining for a long time, show Zigzag growing patterns with open innovation dynamics. First, apples started from personal computer (PC) company, which was based on open innovation because The Apple 1, Macintosh and other PC were made out standardized components. After a few times, it decreased in sales until it produced iPod based on outside in several open innovations in that Tony Fadell developed the idea and concept, and Apple hired a 350-person team and partners from Philips, Ideo, General Magic, Apple, Connectix and WebTV to develop the iPod system (Gassmann et al., 2010). After arriving at the peak in iPod, it moved to iPhone in smart phone industry on 2007, which was based on buying several components related companies including introduction of Siri as a feature inside the new iOS system in 2012 even though Apple developed most of the iPhone's hardware and software in-house, which lead to the filing of >200 patents including for instance multi-touch screen, scrolling and zooming (Remneland-Wikhamn et al., 2011). After then, when Apple arrived at peak at smart phone industry, it changed its directions with iPad. The Zigzag patterns of growth of Apple shows the essential growth types under open innovation dynamics as Apple used diverse open innovation channels such as inviting persons, using M&A, or building up value channel open innovation system etc. whenever it chanced the Zigzag growing direction like Fig. 5 (Bogers et al., 2019).

Second, even though Google started from the founders' idea until Google search engine, Google Map was developed through the acquisition of Where2Technology, a map service company based in Sydney which was originally from a Danish Software engineer Jens Eilstrups Rasmussen in 2005 (Yang et al., 2018). The purchase of Android for $50 million in 2005 gave Google the biggest presence in smartphone operating with the distribution of the first version of Android OS in November 2007 (Martin, 2016). Community-Driven value creation-based value capture company YouTube became a kind of contents business model of Google after acquired on 2006 at $1.65billion even though the M&A of YouTube was a kind of Technological M&A (Chesbrough and Appleyard, 2007; Jo et al., 2016).

Third, Microsoft (MS) which started from DOS operation system (OS) moved to window OS from the outside-in of graphical interface OS from Apple and others (Isaacson, 2011). MS office program had chances to be distributed world widely by inside out open innovation for other firms or agencies to make connection with the program, which was based on the learning effect of MS Window. MS expanded its business model to cloud service based on long time history of M&A outside in open innovation such as Hotmail in 1997, Visio Corp in 2000, Navision in 2002, aQuantive in 2007, Fast Search & Transfer in 2008, Skype Technologies in 2011, Nokia Devices in 2013, Mojang in 2014, and LinkedIn 2016 (Dolata, 2017).

In fact, the growth of firm with open innovation dynamics is not linear nor essential. The growing pattern of firms in open innovation dynamics is zigzag like Fig. 5. And, the sustainable growth of firm could not be obtained automatically just by the acceptance of open innovation, but be gained by careful open innovation strategy selection and efforts continuously by firms. Growing of firm could not be maintained forever just with open innovation dynamics because there is the possibility of collapse of firm by failing to conquer the complexity or cost of open innovation with one time of 'zig' or 'zag', or just limited times of zigzag.

5. Causal loop modeling of inter-rationality

5.1. Evolution of causal loops during the transformation from closed to open innovation

Forrester's market growth model which illustrates system dynamics models including changes with the progress of time and the parts interacting to create a progression of system conditions, portrays bounded rationality because it is based on partial information and rules of thumb (Forrester, 1958, 1968; Morecroft, 1983, pp. 11–12). Causal loops arise when we seek to understand the workings of a complex system by breaking the analysis into component subsystems and mechanisms (Grimm et al., 2006; Simon, 1997). Specifically, Chesbrough (2019) portrayed the open innovation knowledge funnel from external and internal technology bases to a firm's current market, new market, and other firm's markets, and this can be considered as the basis of causal loops in an open innovation context (Marx, 2004).

Neoclassical rationality makes strong and unlikely assumptions about economic agents. Namely, it is assumed that 1) computation ability is limitless, and all entities are the same; 2) all information is known, and all entities have perfect information; and 3) objectives are clear, that is, they do not change over time and are comparable between agents. Under the closed innovation paradigm, all economic agents transfer their own internal research to current markets via new product development based on all information that exists (Fig. 6). However, in the real world, agents have limited understanding, and data are limited, as is computational power.

Bounded rationality makes weaker, more realistic assumptions as follows: 1) economic entities are bounded in their rationality, but are comparable; 2) the computational ability of agents is limited; 3) information availability is limited; 4) objectives can vary among agents, but remain comparable. It is believed that even though these assumptions are more realistic, they still cannot entirely reflect the real world because it is still assumed that agents are comparable, even though agents vary greatly in reality. Fig. 7 shows how semi-open innovation occurs under bounded rationality. Limited information can come in from outside the system, such as outside research or new developments. Additionally, information available in the current market can be used to provide feedback for new product development or internal research.

5.2. Short-term negative effects and long-term positive effects in the causal loop of inter-rationality

It has been suggested that inter-rationality is generally observable in the open innovation paradigm of the fourth industrial revolution (Chesbrough, 2003). Given the new realities of rapid growth in computational power and data availability, the inter-rationality approach can be applied more effectively. AI is an important example and, hence, will be considered below.

In the short-term, open innovation processes will follow the inverted-U-shaped curve, whereby there is a negative impact on markets. More specifically, the open innovation paradox is likely to be observed (upper right section of Fig. 8; Laursen and Salter, 2014). When a firm initially enters a new market, it will struggle to earn revenue because it is a new competitor, and offerings still need to be developed. By applying open innovation strategies, a firm can grow its presence in other markets

Fig. 6. Closed innovation under neoclassical rationality.

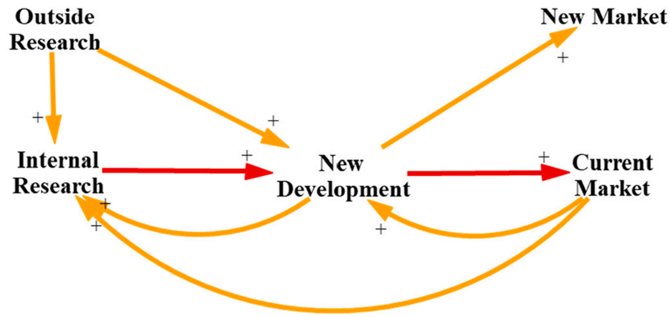

Fig. 7. Semi-open innovation under bounded rationality.

based on internal/external research and new product development. If the new market has some "substitute" characteristics with the firm's current market, then the risk of harming the firm's position in its current market exists. Furthermore, even after open innovation's positive effects begin to accrue, there will be a point at which too much openness benefits competitor firms more, thus harming the firm's position in its old market and new markets.

Fig. 9 clarifies the need to balance the loop through activities in other markets like three short term balancing loops of open innovation with other markets. This will mitigate the impact of the inverted-U-shaped effects of open innovation.

In the long term, positive impacts of entering new markets will appear like the upper-left sections of Fig. 8. By following an open innovation strategy, the firm's presence in new markets can grow more effectively because internal external research and other new developments can all be utilized for innovation. This form of growth at new markets can positively affect the entire related technology streams in the long term. For example, the development of battery technology and AI is now promoting new disruptive innovations in the automobile industry, such as electric and autonomous cars. Growth in other markets can boost internal and external research, though this is a long-term process. The achievement of this development is represented in the upper left section of Fig. 9. Meanwhile, three long-term and positive reinforcing loops linked open innovation with other markets like in Fig. 9.

6. Logical reasoning of inter-rationality

The simulation procedure of inter-rationality here is not validation of inter-rationality but the logical reasoning of inter-rationality because the validating in modeling is typically comparing the model output against reality to demonstrate the capacity to reproduce certain trajectories or stylized facts. However, through this logical reasoning of inter-rationality, the diversity of zigzag growth under inter-rationality can be forecasted.

Thereby, the overview, design concepts, and details protocol are applied, and the latter is a protocol developed as a standard for describing social simulations and ABMs (Grimm et al., 2006; Schmid, 2015). There are four parameters in the simulation: 1) network-members known as the total number of agents; 2) number-of-iterations known as the total time to evolve; 3) open innovation (OI)-breadth known as maximum radius for each agent to find partners, originally defined as "the number of external sources of search channels that firms rely upon in their innovative activities," which ranges from 0 to 100 proportional to total radius of patch; 4) open innovation (OI)-depth, which is defined as "the extent to which firms draw deeply from the different external sources," and ranges from 0 to 100 % (Laursen and Salter, 2006).

The first step of the simulation process is to create agents as the set of

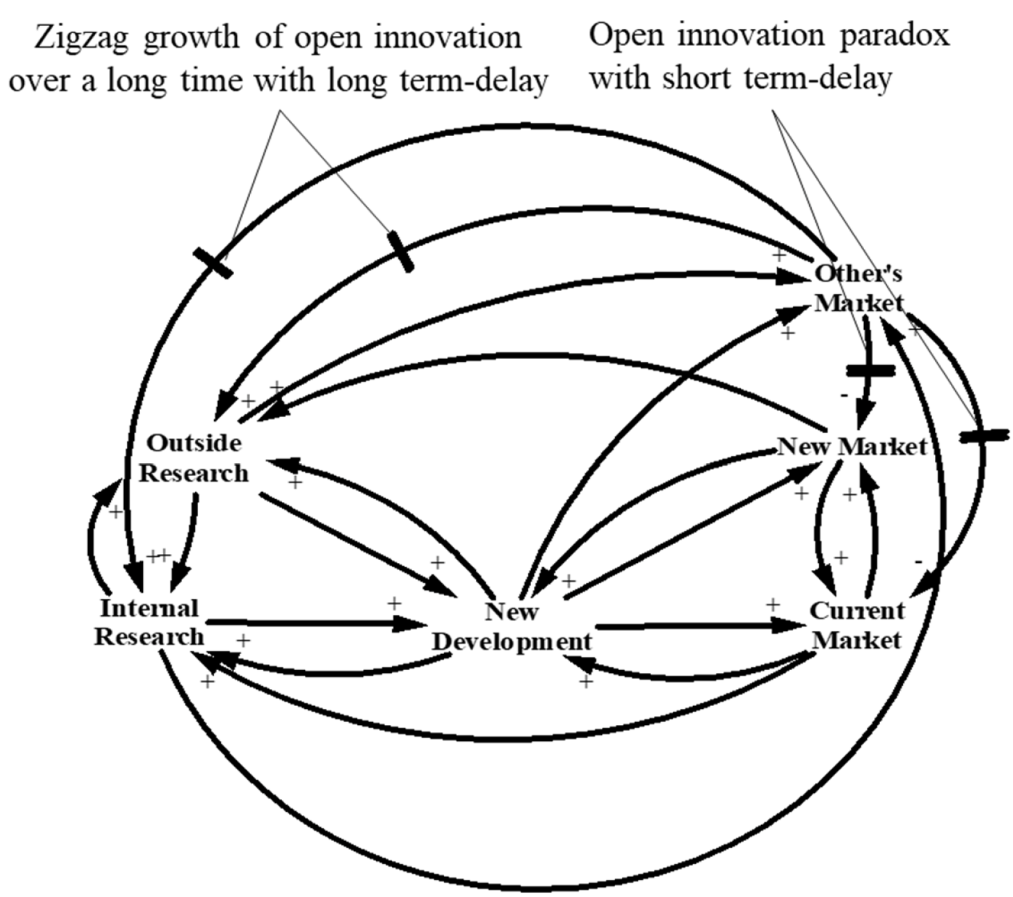

Fig. 8. Open innovation under inter-rationality.

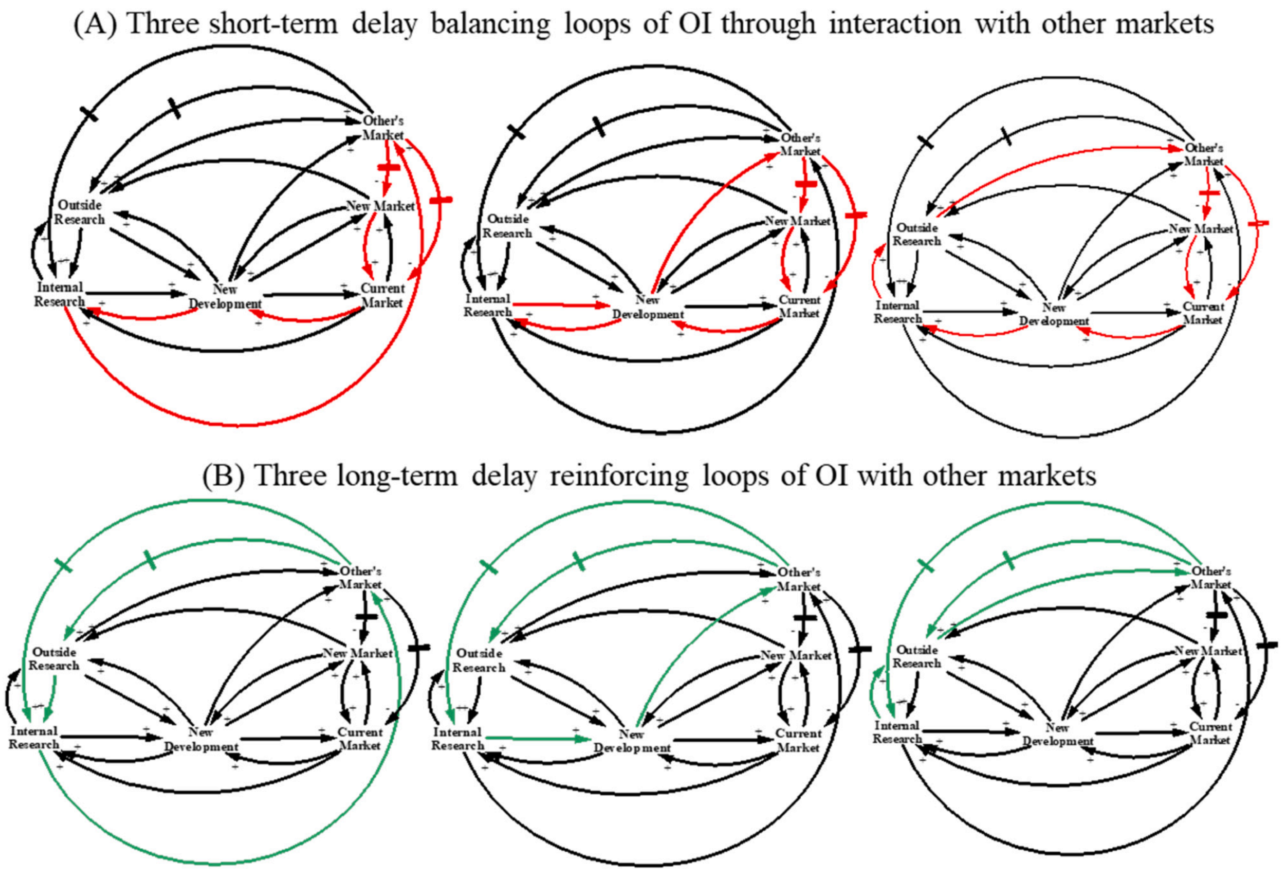

Fig. 9. Three short-term balancing loops and three long term reinforcing loops. OI = open innovation.

network members. Second, the process requires looping through the following up to the number-of-iterations as explained here. 1) Partner search: Each partner-less agent randomly finds another similar agent within the radius OI-breadth, so dyadic random connections are created because this simulation only considers dyadic connections for simplification. 2) Create open innovation performance: Each partnership conducts open innovation performance and as time progresses, the innovation performance evolves according to the inverted-U curve. 3) Update partnership: When the performance of partnership goes negative by the inverted-U curve, the dyadic partnership ends by ending it. 4) Calculate the total performance of all agents: Sum and accumulate the performance-of-collaboration of all partnerships.

This simulation has minimum conditions defined based on past research on open innovation. For fixed OI-depth, OI performance Q_1 by OI-breadth is an inverted-U curve (approximated as a quadratic equation): $Q_1(OI - breadth) = - OI - breadth * (OI - breadth - 2 * Threshold - of - OI - breadth)$.

For fixed OI-breadth, OI performance Q_2 by OI-depth is an inverted-U curve (approximated as a quadratic equation): $Q_2(OI - depth) = - OI - depth * (OI - depth - 2 * Threshold - of - OI - depth)$.

For fixed OI-breadth and OI-depth, OI performance Q_3 as a function of time is an inverted-U curve (approximated as a quadratic equation): $Q3(t_c) = initial - cost + growth - scaler * t_c * (2 * Threshold - of - OI - time - t_c)$. t_c is a local cooperation time, meaning a connection term whose value is 0 when the collaboration of two agents starts and increases until the partnership ends.

When two agents have a partnership, the collaborative performance is defined by the inverted-U curve as a quadratic curve:

$$\begin{aligned} Q(r, d, t_c) &= Result_{OI-breadth} * Result_{OI-depth} * Result_{OI-time} \\ &= Q_1(r) * Q_2(d) * Q_3(t_c) \\ &= [-r(r - 2 * T_B)][-d(d - 2 * T_D)][a_0 + a_1 t_c(a_2 - t_c)] \end{aligned}$$

Here, r is a variable of OI-breadth, d is a variable of OI-breadth, and t is a time variable. T_B is a threshold of OI-breadth, T_D is a threshold of OI-depth, and $\frac{a_2}{2}$ is a threshold of OI-time. a_0 is the initial cost so that $a_0 \le 0$.

a_2 decides the time duration of the partnership, since $Q(a_2) = a_0 \le 0$ and the partnership will end before $t = a_2$. $Q''(t) = -2a_1$ for fixed r and d, and so a_1 decides the curvature and the maximum value of the inverted-U curve. When an agent finds a partner to collaborate, the variables $a_0, a_1,$ *and* a_2 are chosen uniformly randomly: $-1 \le a_0 \le 0$, $1 \le a_1 \le 10$, *and* $1 \le a_2 \le 10$.

Simulation results for various OI-breadth and OI-depth such as 10 %, 30 %, 50 %, and 90 % with network members 100 and number of iterations 1000 are presented in Fig. 10.

The simulation results (Fig. 11) show that the performance of open innovation grows upward as zigzag until 50 % ratio of OI-breadth, and OI-depth. However, in real economies with the cumulation of open innovation performance, zigzag growth will be continued if the OI-breadth and OI-depth do not arrive at 0 like the cumulative OI performance in Fig. 11. Any point at the zigzag growth curve is not the maximum point even though it has a high performance compared to other points nearby. By zigzagging from the inter-rationality, the open innovation performance of a firm can arrive at high performance even though it is not the maximum, and the firm can grow continuously with the cumulation of open innovation performance.

7. Discussion

There are three key aspects of the open innovation interactions on

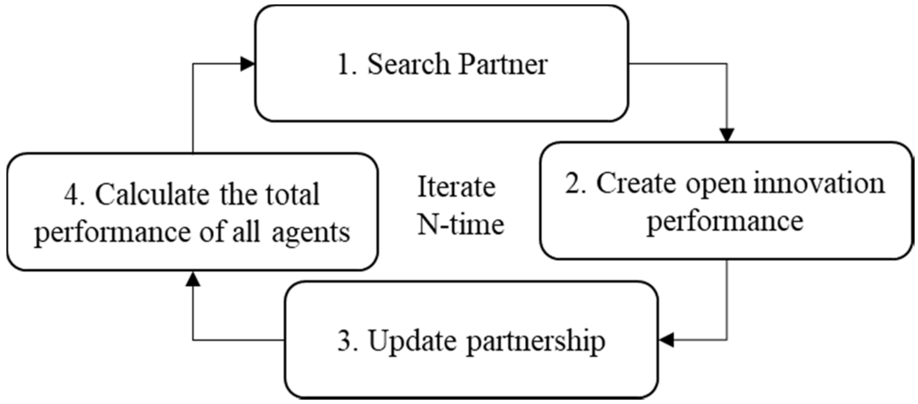

Fig. 10. Diagram of inter-rationality simulation process.

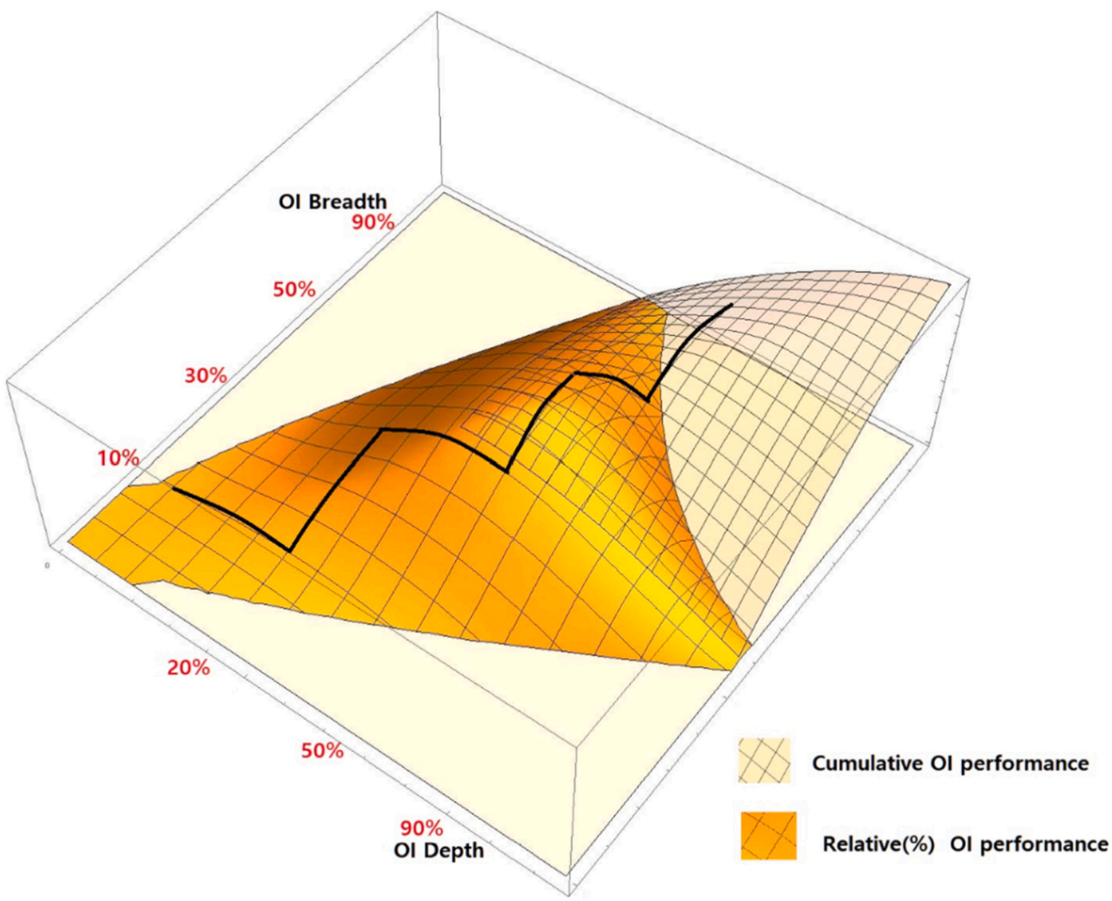

Fig. 11. Simulation results for zigzag growth. OI = open innovation.

behalf of inter-rational agents, which generate the zigzag growth pattern in the economic system (Fig. 11). First, each inter-rational agent has their own characteristics that cannot be compared to others. In practice, this is represented by, for example, a small start-up, which can have its own creative business model, market, or technology, which can also be combined with other SMEs' or even big businesses' knowledge via open innovation channels to generate creative emergent synergies. Firms that are competing in a well-established market have their own strengths and opportunity sets. These can be leveraged if the firm interacts with others through open innovation channels such as partnership, joint venture, patent licensing, and mergers and acquisitions. Nonetheless, under inter-rationality, it is assumed that any economic agent may have their own strengths and opportunities, which are valuable in an open innovation context, and even some agents may seem weak comparatively.

Second, it should be noted that, even though this study has emphasized the positive, overall impact of inter-rationality and open innovation, it is still possible for the open innovation paradox to occur. Open innovation participants risk the invasion of others into their current market or the new markets they are entering because the agent's creative characteristics are, by definition, more accessible to other firms. However, the enhanced availability of computational power may enhance bounded rational agents to assess and mitigate this risk.

Third, to ensure that the expected overall positive result of creative convergence occurs from inter-rational agents' open innovation actions, it is vital to leverage internal/external research and new developments (Fig. 12). The bounded rationality characteristics of inter-rationality still enable agents to stop open innovation prior to the open innovation paradox appears and affects them negatively. At this point, the agent can move to other open innovation channels and re-commence early-stage open innovation activities, thus avoiding the open innovation paradox. The zigzag growth pattern of open innovation revenues is the accumulation of open innovation revenues from a range of open innovation channels.

In the end, economics systems at a national, regional, or sectoral level can all grow according to the zigzag pattern of open innovation. The growth rate in the economic system is expected to fluctuate from the micro perspective of an individual firm and will not follow a linear growth pattern from a macro perspective. The growth of the economic system when open innovation is practiced by inter-rational agents follows a zigzag pattern. This can be expected to be a sustainable form of economic growth.

8. Conclusion

8.1. Implications

8.1.1. Theoretical implication

In this study, we developed the conceptual model of inter-rationality which is a kind of bounded rationality in open innovation dynamics. Bounded rationality which had been conceptualized by Herbert Simon who had been the academic advisor of Henry Chesbrough who developed the concept open innovation in 2003, became of a milestone of the development of Non-classical economics such as the Keynesian economics, the Schumpeterian economics, the experimental economics, or the post-Marxist economics. Similarly, inter-rationality could be the precondition or essence of economics, political economics, social science, or open innovation engineering in the digital transformation era, or the 4th industrial revolution paradigm as the economic human's dominant type of bounded rationality. For example, the inter-rationality could be used as the base of the macro or micro dynamics of economics in digital transformation. In addition, the inter-rationality could be the starting point of the experiment for open innovation dynamics to conquer the arrow information paradox, or the experiment for finding out zigzag growth pattern of any firm to survive sustainably.

8.1.2. Practical implication

The challenge of the growth limits that can affect an economy are considered to underpin the importance of identifying sustainable growth patterns, called the zigzag pattern which is motivated by inter-rationality under open innovation dynamics. Applying the concept of inter-rationality in the model leads to the identification of the economic system's zigzagging growth pattern, which is different from previously conceptualized fluctuating or linear growth patterns. The zigzag growth pattern resulting from open innovation dynamics as defined in this study suggests a way to overcome the limits to growth in the economic system. If any firm chooses open innovation strategy which can be good for it at the moment under the inter-rationality, it could find out the zigzag growth pattern for itself to conquer the growth limits.

8.2. Limitations and future research topics

8.2.1. Limitations

In this study, the conceptual model of inter-rationality in open innovation dynamics was only logically reasoned by mathematical modeling, causal loop modeling, and simulation. Thus, the applicability of this model at the firm level or in different contexts and using different modeling approaches at an economic system level are future research topics. Second, empirical research to identify concrete cases and real-life examples of the zigzag growth pattern, which is defined from a theoretical perspective in this study, is a significant avenue for future research. Third, this study is only the first step toward developing hypotheses that will enable the dynamics of open innovation to be understood in the context of economics.

8.2.2. Future research topic

There are a lot of future research questions that focus on understanding the meaning and key conceptual points of inter-rationality as follows. First, inter-rationality can be used directly in building up open innovation strategy of firms by checking inter-rationality points, and zigzag growth direction with better timing for that. Second, difference of zigzag growth pattern according to belonging industry or sectorial innovation system could also be future research topic. Third, the inter-rationality could be studied according to the difference of macro and micro economic level, or the differences of national innovation system, regional innovation system, or sectorial innovation system and etc. Fourth, inter-rationality could be researched to find out the matching mechanism between technology and market in the context of micro and macro open innovation dynamics. Fifth, inter-rationality could be used to develop and fascinate the human-artificial intelligence model which can be used at the next general paradigm of car industry, electronics industry, or electric home appliances.

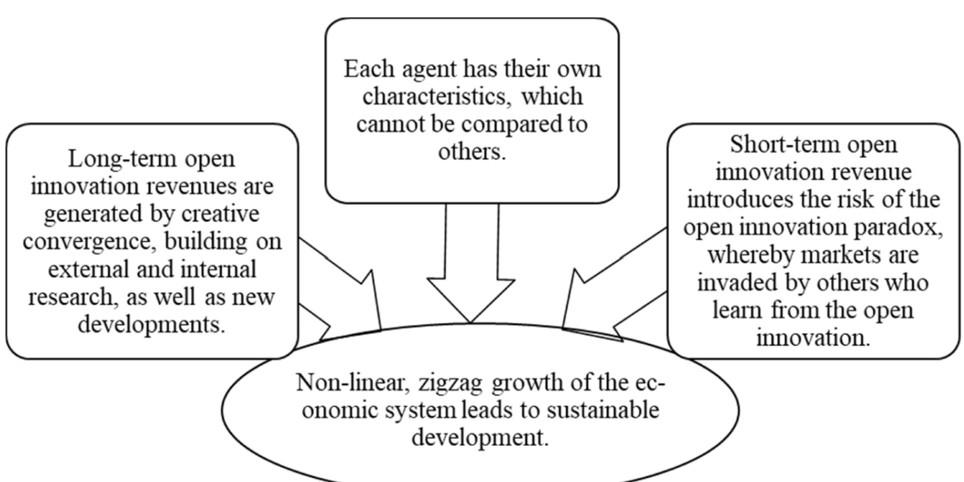

Fig. 12. The three aspects of inter-rationality that lead to a zigzagging economic growth pattern.

Declaration of competing interest

None.

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