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Collective Intelligence: An Emerging World in Open Innovation

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Abstract: Responding to the lack of empirical research on the effect of collective intelligence on open innovation in the fourth industrial revolution, we examined the relationship between collective intelligence and open innovation. Collective intelligence or crowd innovation not only produces creative ideas or inventions, but also moderates any firm to innovate inside-out, outside-in, or in a coupled manner. We asked the following research questions: Does collective intelligence (or crowd innovation) motivate open innovation? Is there any difference in the effect of collective intelligence on open innovation by industry? These research questions led to the following three hypotheses: (1) Collective intelligence increases the performance of a firm, (2) collective intelligence will moderate the effect of open innovation, and (3) differences exist between the automotive industry and the pharmaceutical industry in these two effects. To empirically examine these three hypotheses, we analyzed the registered patents of these two industries from 2000 to 2014 over a 15-year period. These automotive and pharmaceutical patents were registered in the B60 category and the A61K category of the Korea Patent office, respectively. Collective intelligence was measured by co-invention. We found differences in the effects of collective intelligence on open innovation between the two industries. In the automotive industry, collective intelligence not only directly increased the performance, but also indirectly moderated the open innovation effect. However, this was not the case for the pharmaceutical industry.

Keywords: collective intelligence; open innovation; moderating effect; automotive industry; pharmaceutical industry

1. Introduction

Collective intelligence started emerging in cyberspace in the 1990s [1]. The neural-network-based computer program, AlphaGo, was trained by a novel combination of supervised learning from human expert games and reinforcement learning from self-games. AlphaGo defeated the human Go champion SaeDol Lee in 2016 with four games to one [2]. The neutral learning process is similar to open innovation in that it motivates creativity by opening new combinations similar to the creativity of open innovation by collective intelligence or crowd innovation [3,4]. Some evidence exists of the contribution of a collective intelligence factor to the performance of human groups [5]. The acquisition of knowledge is becoming distributive; it is not located in any given place and therefore not transferred or transacted per second, but rather consists of networks of connections formed from experience and interactions with a knowing community as a collective intelligence [6]. Science is also collective because it depends on and has tried to institutionalize the free and open exchange of information. For example, when scientists make an important new discovery or try to experimentally prove a critical hypothesis, they do not, in general, keep that information to themselves. By doing so, they can ponder its meaning and derive additional theories [7]. In addition, the U.S. federal government has successfully implemented open innovation concepts in the private sector to substitute solutions from previously untapped problem solvers and to tackle complex social and technical public management problems [8].

Under this environment, is there any relationship between collective intelligence and open innovation? If collective intelligence or crowd innovation not only produces creative ideas or inventions, but also lets any firm to innovate inside-out, outside-in, or in a coupled way, it should be motivated by invention or research and development (R&D) steps. We thus set up the following research questions: Does collective intelligence (or crowd innovation) motivate open innovation? Is there any difference in the relationship between collective intelligence and open innovation in different industrial sectors?

2. Literature Review, Hypotheses, and Research Framework

2.1. Literature Review and Hypotheses

Explicit collaboration on academic papers and research projects is not the only factor that makes science a collective enterprise, because when scientists make an important new discovery or experimentally prove some hypothesis, they do not, in general, keep that information to themselves [7]. Collective intelligence can be broadly defined as a group of individuals acting collectively that seems intelligent, which includes the following four factors: (1) Crowd as who; (2) hierarchy (or management), money, love, or glory as why; (3) collaboration, contest, or collaboration as how to create; and (4) group decision or individual decisions through a market or social network as how to decide [9,10]. The use of Internet platforms and Web 2.0 technologies has allowed for another form of participation, which is possible irrespective of opening hours, meeting places, jurisdictional boundaries, places of residence, and physical presence; this is called crowd innovation in public administration with broad participation in public service [11]. The emergence of Web-based tools has enabled experimenting with a number of different mechanisms for tapping into the decision-making capabilities of the collective intelligence at a firm under condition such as a balance between diversity and expertise, and a distinction between decentralized and distributed decision making [12]. According to a report on the results of an investigation about informal public-side communications that occurred in the aftermath of the 16 April 2007 Virginia Tech (VT) shooting, collective intelligence was found to operate effectively in a disaster situation [13].

In research, evidence for a collective intelligence factor in the performance of human groups has been found, specifically that collective intelligence is higher than average member intelligence and maximum member intelligence [5]. The algorithms used to develop a collective mental map have been researched to implement collective intelligence on the Web [14]. Other research developed rating scales for collective intelligence in innovation communities to analyze an effective idea rating and selection mechanism [15]. Another study introduced a crowd ideation system where experts monitor incoming ideas through a dashboard and offer high-level inspiration to guide ideation as a method to improve crowd innovation with real-time expert guidance [16]. According to the emerging science of how to design a collective intelligence (COIN), a COIN is a large multi-agent system that has no centralized communication, and the authors provided a world utility function that rates the possible histories of the full system [17].

Hypothesis 1. *Collective intelligence increases the performance of a firm.*

According to the literature, collective intelligence increases not only the performance of public service, risk treating, and science, but also the performance of a firm. Many researchers are thus trying to develop collective intelligence software (SW) systems. If all knowledge is explicit, i.e., capable of being clearly stated, then we cannot know a problem or look for its solution [18]. Polanyi's thesis, "We can know more than we can tell", cannot be escaped [19]. Collective intelligence can thus increase the open innovation effects because the crowd can treat tacit knowledge more effectively than others, for example, individual researchers, if we accept that open innovation has been a valuable concept for many firms and in many contexts [20]. A growing amount of scientific research is being conducted in an open collaborative fashion in projects sometimes referred to as crowd science, citizen science, or networked science. Examples include a large-scale collaborative project involving thousands of participants who have advanced our understanding of protein folding at an unprecedented speed and the Galaxy Zoo project involving over 250,000 volunteers who helped with the collection of astronomical data [21]. Even though the effects of collective intelligence were measured by a multi-criteria rating scale, we can determine the direct effect of collective intelligence or the indirect effects of the open innovation strategy of a firm that is motivated by collective intelligence [22].

The redundancy principle and design for the emergence principle are required for crowdsourcing collective intelligence to create social value or additional knowledge; these two conditions are the core of open innovation [23,24]. Crowdsourcing as a "collective intelligence system" is characterized by three components: (1) An organization that directly benefits from the work of the crowd, (2) the crowd itself, and (3) a platform able to link the two together and provide a host for the activity throughout its lifecycle that can directly motivate citizen participation and indirectly motivate open innovation for opportunities for planning or others [25]. Collective intelligence through crowdsourcing can thus enlarge the open innovation effect in marketing, human resource management (HRM), or change management at the firm level [26]. Permission-less innovation as the general policy default can motivate collective intelligence platforms directly and indirectly [27].

If we possess all the relevant information, if we can start from a given system of preferences, and if we command complete knowledge of the available means, the problem that remains is purely one of logic that can be easily answered under the fourth industrial revolution because crowdsourcing activities can operate best when an individual or company gives the crowd something it wants [28–30]. Based on portfolio theory, Renaissance Technologies (New York, NY, USA) developed a crowd investment platform and achieved global success [31–33]. A crowd can perhaps innovate without limits if permission-less innovation is possible, such as in the Rob-hand case, and if we identify and remove barriers for the crowd to enter and innovate while relying on existing legal solutions and the common law to solve problems, even in the peer-to-peer electronic cash system [27,34]. Inventor mobility can be a kind of trigger of knowledge spill-overs and can motivate open innovation with the mobility of collective inventers [35].

Hypothesis 2. *Collective intelligence will moderate the effect of open innovation.*

According to the literature review, collective intelligence will positively moderate the effect of open innovation on the performance of the firm. We therefore present this second hypothesis.

2.2. Research Framework

2.2.1. Independent Variables

We have two independent variables: Collective intelligence and open innovation. A patent inventor network that is connected with collective intelligence is not bigger than patent applicant citation networks, even though the patent inventor network grows with the increase in the industry to which it belongs [36]. At present, both the need for large numbers of patented inventions to be combined in any single product and the need for collective intelligence to respond to big science and the complexity of modern technology are increasing [37,38].

Collective intelligence (CL) can be built up by the standardized multiple between the breadth of CL (BCL) (the ratio of two or more inventors having patents in a firm) and the depth of CL (DCL) (the average inventors per patent of the firm).

Co-patent application means technological collaboration in inventive activities, which is a kind of open innovation [39]. Co-ownership of patents can be conducive to a high quality of joint patents, which can increase the performance of a firm, such as sales or market dominance [40]. Co-ownership of intellectual property explores the value-appropriation and value-creation implications of co-patenting with different partners [41]. Shared intellectual property rights on patents, which occurs when two or more assignees are found on one single patent application, usually occurs as a result of collaboration and can thus be viewed as a special result of collaborative activity—open innovation [42–44].

Open innovation (OI) can be measured by the standardized multiple between the breadth of OI (BOI) (the ratio of two or more applicants having patents in the firm) and the depth of OI (DOI) (the average applicants per patent of the firm).

2.2.2. Dependent Variables

We used three different dependent variables that originated from patents to fully measure the effect of open innovation and collective intelligence because the value of patents as an indicator to measure innovative performance is increasing [45]. Basically, patenting figures can be interpreted as an indicator of innovation [46]. For example, the Herfindahl–Hirschman index (HHI) of patents and the relative patent position (RPP) have nonlinear and monotonically positive influences upon corporate performance, whereas the effect of patent citations is nonlinearly U-shaped [47,48]. The significance of technology as support for selecting R&D projects can be measured by patent index analysis and technology transferability can be measured by patent citation analysis [49].

The diversity of technological capabilities that can be measured, such as the sub-international patent classification (IPC) number, can enhance the market value or sales growth of firms [50,51]. In addition, patent diversity, which can be calculated from the frequency of patent co-classification by a variable such as the number of sub-IPC numbers, can be a kind of predictor of regional innovativeness [52]. The IPC classification at the group level can be used as a measure of novelty in technological knowledge origins [53].

First, we used the average of the sub-IPC number of the firm as a dependent variable. This is useful for measuring the increase in the technological quality of the firm. The economic value of patents increases with an increase in patent lawsuits, that is, patent conflicts, in the Korean automotive, robotics, and aviation industries [54]. Second, we used the ratio of conflicted patents for a firm. An increase in the ratio of a firm's conflicted patents may indirectly indicate an increase in the economic value of the patents of the firm. With the growth of patenting at universities in the U.S. as a result of the Bayh–Dole Act of 1980, licensing by U.S. universities has increased, serving as an indicator of the commercialization of university patents [55]. Third, we used the ratio of transferred patents of the firms, which means the commercialization of patents of the firms. This directly reflects the economic value of the patents of the firm.

2.2.3. Control Variable

We selected the number of patents as a control variable, which has a direct relationship with the size of the firm or the year of the firm.

2.2.4. Difference between the Automotive and Pharmaceutical Industries

We considered the peculiarities of the external environment in which a firm operates, and there are inter-industry differences in the implementation of open innovation [56]. Most technological knowledge is not information that is generally applicable and easily reproducible, but rather is specific to firms and applications, cumulative in development, and varied amongst sectors in source and direction [57].

In Korea, the automotive industry is a mature industry that is more than 40 years old. However, the pharmaceutical industry of Korea is still emerging. Therefore, open innovation and collective intelligence will have a positive effect on firm performance in the automotive industry [54], but will not have an effect in Korea's pharmaceutical industry [58–60]. This explains how an intrapreneurial regime contributes to the emergence of any new industry as the intrapreneurial regime is characterized by a higher degree of stability, is denser and has hierarchically structured networks of innovative firms, with a dominant role of established firms, and a lower rate of entries and exits [61]. Therefore, in an after-growth industry such as the automotive industry in Korea, collective intelligence can motivate open innovation and have a positive effect on the performance of a firm.

Hypothesis 3. *Differences exist between the automotive industry and the pharmaceutical industry in moderating the open innovation effects by collective intelligence.*

To summarize our discussion, our research framework is presented in Figure 1. In this study, we used three different dependent variables to measure firm performance: The technological value by the number of sub-IPC, the potential market value of firm performance by patent dispute, and the real market value of firm performance by patent technology transfer.

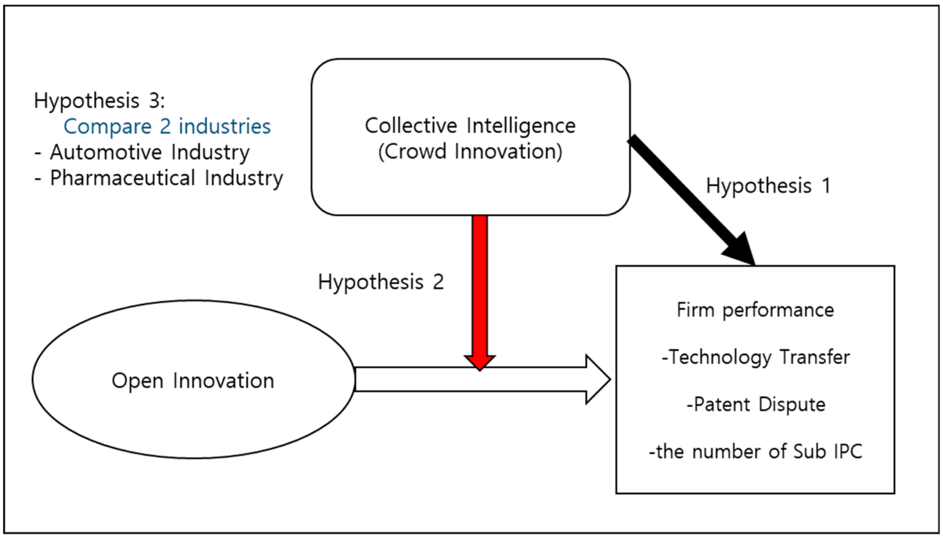

Figure 1. Research framework.

Second, we measured the direct and indirect effects of CL and, that is, the moderating effect of CL on the open innovation effects as Hypotheses 1 and 2. Third, we compared the difference between the automotive industry and pharmaceutical industry of Korea, examining the difference between a mature industry and immature industry.

2.3. Research Scope and Method

Based on the patents that were registered at the Korea Patent Office, we targeted automobile patents in the B60 category and pharmaceutical patents in the A61K category, which were selected from patents registered during a 15-year period from 2000 to 2014.

According to Table 1, the automotive industry has more patents, fewer firms, and a larger per firm patent number than the pharmaceutical industry. However, the number of patent applicants including firms and individuals in the automotive industry is smaller than in the pharmaceutical industry (10,978 versus 14,679). The average patents per applicant including firms and individuals in the automotive industry are also higher than in the pharmaceutical industry (4.57 versus 2.61).

Table 1. Technical statistical analysis patent data overview.

Division	Automobile (B60)	Pharmaceutical (A61K)
Total number of patents of firms and individuals	50,126	38,244
Number of patents of firms	40,336	25,772
Number of patent applicants including firms and individuals	10,978	14,679
Number of firms	3844	5265
Average patents per applicant, including firms and individuals	4.57	2.61
Average patents per firm	10.49	4.89

According to Table 1, the automotive industry in Korea is an after-maturity industry, even though the pharmaceutical industry of Korea is pre-maturity industry because the pharmaceutical industry has a higher firm number and lower number of patents per firm than the automotive industry.

As presented in Table 2, the automotive industry is larger than the pharmaceutical industry in the descriptive statistics of the independent variable and moderating variable, although it is smaller in the dependent variables. With these data and variables, we conducted the regression analysis.

Table 2. Descriptive statistics.

Variable		Automotive Industry			Pharmaceutical Industry		
		Mean	SD	Frequency	Mean	SD	Frequency
Dependent Variables	Ratio of Transferred Patents (RTP)	68.077	39.849	98	64.716	38.185	1075
	Ratio of Disputed Patents (RDP)	38.616	38.962	359	54.297	36.297	1432
	Average Number of Sub IPC (AN-SIPC)	1.691	0.714	3844	1.848	0.685	5265
Independent Variable	Open Innovation (OI) = zBOI × zDOI	0.828	1.767	3844	0.700	1.572	5265
Moderating Variable	Collective Intelligence (CL) = zBCL × zDCL	0.700	0.777	3844	0.122	0.587	5265

Note: BCL = breadth of collective intelligence; DCL = depth of collective intelligence; BOI = breadth of open innovation; DOI = depth of open innovation.

3. Automotive Industry Analysis

3.1. Correlation Analysis of the Automotive Industry

According to Table 3, correlations exist between open innovation (OI) and the ratio of disputed patents (RTP), between the ratio of disputed patents (RDP) and collective intelligence (CL), and between the collective intelligence and average number of sub-IPC (AN-SIPC). Attention should be paid to the correlation between OI and CL as we analyze and discuss these results. Finally, correlations exist between CL and the RDP, and between CL and AN-SIPC.

Table 3. Correlation of the automotive industry.

Variable	Ratio of Transferred Patents (RTP)	Ratio of Disputed Patents (RDP)	Average Number of Sub IPC (AN-SIPC)	Collective Intelligence (CL) = zBCL × zDCL	Open Innovation (OI) = zBOI × zDOI
Ratio of Transferred Patents (RTP)	1				
Ratio of Disputed Patents (RDP)	0.746 **	1			
Average Number of Sub IPC (AN-SIPC)	−0.038	0.078	1		
Collective Intelligence (CL) = zBCL × zDCL	0.114	0.323 **	0.044 **	1	
Open Innovation (OI) = zBOI × zDOI	0.360 **	0.300 **	−0.028	0.188 **	1

Note: ** denotes correlation is significant at the 0.01 level (two-tailed).

3.2. *Moderating Effects*

3.2.1. Automotive Industry in the Average Number of Sub-IPC (AN-SIPC)

According to Table 4, in the automotive industry, CI has a positive effect on firm performance with respect to the number of sub-IPC. Therefore, Hypothesis 1 of the number of sub-IPC is accepted. In addition, in the automotive industry, CI has a moderating effect on the open innovation effect of firm performance with respect to the number of sub-IPC, thus supporting Hypothesis 2 of the number of sub-IPC is accepted.

Table 4. The moderating effect of the automotive industry on the average number of sub-international patent classification (sub-IPC) (AN-SIPC).

Dependent Variable	Average Number of Sub IPC (AN-SIPC) (β)		
	Level 1	Level 2	Level 3
Independent Variable Open Innovation (OI) = zBOI × zDOI	−0.028	−0.038 *	0.041 *
Moderating Variable Collective Intelligence (CL) = zBCL × zDCL		0.052 **	0.045 **
Interaction Term zOI × zCL			−0.017

Note: β = standard coefficient, 2,3: Natural log; ** $p < 0.01$ (two-tailed).

3.2.2. Automotive Industry in the Ratio of Disputed Patents (RDP)

According to Table 5, in the automotive industry, CI has a positive effect on firm performance with respect to the number of sub-IPC. Therefore, Hypothesis 1 of the ratio of disputed patents is accepted. In the automotive industry, CI has a moderating effect on the open innovation effect of firm performance with respect to the ratio of disputed patents. In other words, Hypothesis 2 of the RDP is accepted.

Table 5. The moderating effect of the automotive industry on the ratio of disputed patents (RDP).

Dependent Variable	RDP (β)		
	Level 1	**Level 2**	**Level 3**
Independent Variable Open Innovation (OI) = zBOI × zDOI	0.300 **	0.215 **	0.253 **
Moderate Variable Collective Intelligence (CL) = zBCL × zDCL		0.251 **	0.276 **
Interaction Term zOI × zCL			−0.096

Note: β = standard coefficient, 2,3: Natural log; ** $p < 0.01$ (two-tailed).

3.2.3. Automotive Industry in the Ratio of Transferred Patents (RTP)

According to Table 6, in the automotive industry, CI does not have a positive effect on firm performance in terms of the ratio of transferred patents. Therefore, Hypothesis 1 of the ratio of transferred patents is rejected. In the automotive industry, CI does not have a moderating effect on the open innovation effect of firm performance with respect to the ratio of transferred patents. In other words, Hypothesis 2 of the ratio of transferred patents is rejected. The Korean automotive industry does not show an open innovation effect in RTP because large companies have dominated this market [55].

Table 6. The moderating effect of the automotive industry on the ratio of transferred patents (RTP).

Dependent Variable	RTP (β)		
	Level 1	**Level 2**	**Level 3**
Independent Variable Open Innovation (OI) = zBOI × zDOI	0.360 **	0.360 **	0.408 **
Moderate Variable Collective Intelligence (CL) = zBCL × zDCL		0.002	0.037
Interaction Term zOI * zCL			−0.107

Note: β = standard coefficient, 2,3: Natural log; ** $p < 0.01$ (two-tailed).

We used three dependent variables in this study to fairly capture the effects of CL in more detail. For the two dependent variables, An-SIPC and RDP, CL has a positive effect on performance and positive moderating effects, which is contrary to the results of RTP. From this, we can observe the effect of CL in the automotive industry, even though direct technology transfers of CL did not appear.

4. Pharmaceutical Industry Analysis

4.1. Correlation Analysis of the Pharmaceutical Industry

According to Table 7, correlations exist between OI and RTP, OI and RDP, CL and AN-SIPC, and OI and CL in the pharmaceutical industry in Korea; whereas OI has correlations with RTP and RDP, CL only has a correlation with AN-SIPC.

Table 7. Correlations of the automotive industry.

Variable	Ratio of Transferred Patents (RTP)	Ratio of Disputed Patents (RDP)	Average Number of Sub IPC (AN-SIPC)	Collective Intelligence (CL) = zBCL × zDCL	Open Innovation (OI) = zBOI × zDOI
Ratio of Transferred Patents (RTP)	1				
Ratio of Disputed Patents (RDP)	0.735 **	1			
Average Number of Sub IPC (AN-SIPC)	−0.055	−0.028	1		
Collective Intelligence (CL) = zBCL × zDCL	0.035	0.039	0.124 **	1	
Open Innovation (OI) = zBOI × zDOI	0.178 **	0.182 **	0.009	0.146 **	1

Note: ** denotes Correlation is significant at the 0.01 level (two-tailed).

4.2. Moderating Effects

4.2.1. Pharmaceutical Industry in the AN-SIPC

According to Table 8, CL has positive effects on AN-SIPC in the Korean pharmaceutical industry. However, there is no moderating effect of CL on the open innovation effect of this industry.

Table 8. The moderating effect of the pharmaceutical industry on the AN-SIPC.

Dependent Variable	AN-SIPC (β)		
	Level 1	Level 2	Level 3
Independent Variable Open Innovation (OI) = zBOI × zDOI	0.009	−0.009	−0.017
Moderate Variable Collective Intelligence (CL) = zBCL × zDCL		0.125 **	0.124 **
Interaction Term zOI × zCL			−0.016

Note: β = standard coefficient, 2,3: Natural log; ** $p < 0.01$ (two-tailed).

4.2.2. Pharmaceutical Industry in the Ratio of Disputed Patents

According to Table 9, CL does not have any effects on the RDP of the Korean pharmaceutical industry. In addition, CL does not have any moderating effects on the open innovation effect of this industry, although an OI effect exists in RDP.

Table 9. The moderating effect of the pharmaceutical industry on the RDP.

Dependent Variable	RDP (β)		
	Level 1	Level 2	Level 3
Independent Variable Open Innovation (OI) = zBOI × zDOI	0.182 **	0.180 **	0.180 **
Moderate Variable Collective Intelligence (CL) = zBCL × zDCL		0.022	0.022
Interaction Term zOI × zCL			0.000

Note: β = standard coefficient, 2,3: Natural log; ** $p < 0.01$ (two-tailed).

4.2.3. Pharmaceutical Industry in the Ratio of Transferred Patents

According to Table 10, CL does not have any effect on the RTP in the Korean pharmaceutical industry. In addition, CL does not have any moderating effect on the open innovation effect of RTP in the Korean pharmaceutical industry.

Table 10. The moderating effect of the pharmaceutical industry on the RTP.

Dependent Variable	Ratio of Transferred Patents (RTP) (β)		
	Level 1	**Level 2**	**Level 3**
Independent Variable Open Innovation (OI) = zBOI × zDOI	0.178 **	0.178 **	0.309 **
Moderate Variable Collective Intelligence (CL) = zBCL × zDCL		0.003	0.004
Interaction Term zOI × zCL			−0.181 **

Note: β = standard coefficient, 2,3: Natural log; ** $p < 0.01$ (two-tailed).

According to Tables 7–10, CL does not have any moderating effect on the open innovation effects of the Korean pharmaceutical industry, such as RDP or RTP. Therefore, even though the CL of the pharmaceutical industry affects AN-SIPC and RDP (accept Hypothesis 1), and there are meaningful OI effects on RDP and RTP, there is no meaningful moderating effect of CL on OI in the pharmaceutical effect (reject Hypothesis 2).

5. Discussion

5.1. Comparative Analysis of the Two Industries

According to Table 11, among the dependent variables, RTP is not suitable in this research because this variable has no meaning in any industry. Except for RTP, among the four dependent variables, three variables have different effects between the two industries. Therefore, Hypothesis 3 can be accepted. The automotive industry shows meaningful CL effects on the firm performance, such as AN-SIPC and RDP. In addition, the moderating effect of CL on the open innovation effects on the firm performance, such as AN-SIPC and RDP, are meaningful in this industry.

Table 11. Comparative analysis of the two industries.

Hypothesis	Dependent Variable	Automotive Industry	Pharmaceutical Industry
Hypothesis 1	AN-SIPC RDP RTP	Accepted Accepted Rejected	Accepted Rejected Rejected
Hypothesis 2	AN-SIPC RDP RTP	Accepted Accepted Rejected	Rejected Rejected Rejected
Hypothesis 3		Accepted	

In contrast, the pharmaceutical industry only shows a useful CL effect on firm performance in terms of AN-SIPC. The pharmaceutical industry does not show any meaningful moderating effect of CL in terms of OI. Therefore, according to Table 1, first, the Korean pharmaceutical industry has matured less compared to the automotive industry. In other words, in this immature industry, CL does not have a meaningful or sufficient effect on the firm performance. Second, in the immature industry, CL does not have a meaningful or sufficient moderating effect on firm performance. Third, between the automotive industry and pharmaceutical industry in Korea, differences exist in the CL direct effects and CL moderation effects. Therefore, if we increase the CL during the maturation of any industry, it will have direct and indirect positive effects on firm performance.

5.2. Collective Intelligence as a New Breakthrough to Increase Firm Performance

First, if any industry matures sufficiently, a positive feedback loop can be constructed between CL and OI, as shown by A in Figure 2. Second, if any industry matures sufficiently in terms of collective intelligence, CL can directly increase the technological value of patents, such as the number of sub-IPC in this research, denoted by B in Figure 2. Third, CL also moderates the growth of the potential market value of patents, such as the dispute of patents, denoted by C in Figure 2. Fourth, these three effects of CL, A, B, and C in Figure 2, increase the real value market value by patent transfer. This means that CL not only increases the technological value of patents, but also the market value of the patent in the end. However, if we do not increase CL, the increase of performance by the direct effect of CL, and the moderating effect of it, does not increase, as in the pharmaceutical industry of Korea. Therefore, firms should set up strategies to increase not only OI, but also CL together.

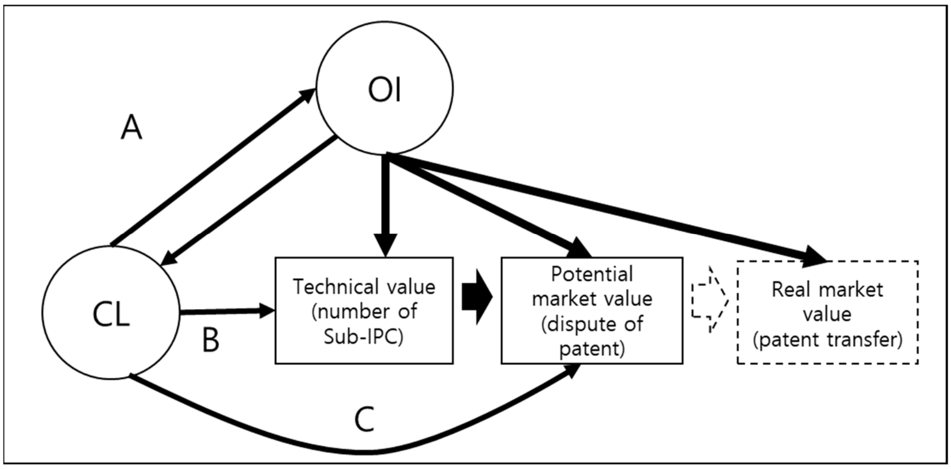

Figure 2. The value of collective intelligence.

Another important implication of this study is the increase in OI possibility by collective intelligence with the maturing of industry, as shown in Figure 3. In early industry, four co-inventers, such as a, b, c, and dm all belong to firm A. At this point, the four inventors co-invent results in traditional collective intelligence. As the industry grows, co-inventor b moves to new firm B. In this step, only one possibility of open innovation exists between firm A and firm B. The possibility of OI between firm A and firm B is high because co-inventors a, b, c, and d know each other well and have common ideas about the co-inventing patent or business model.

As the industry matures, co-inventors c and d also move to new firms C and D, respectively. In this step, there are 11 possibilities for OI among firms A, B, C, and D, like in Figure 3. The possibility of OI among firms A, B, C, firm D is still high because a, b, c, and d were co-inventors of one patent or business model, and they are still in the same industry, even though they are not in the same firm. Therefore, according to Figure 3, the value of collective intelligence for open innovation will increase with the maturing of industry.

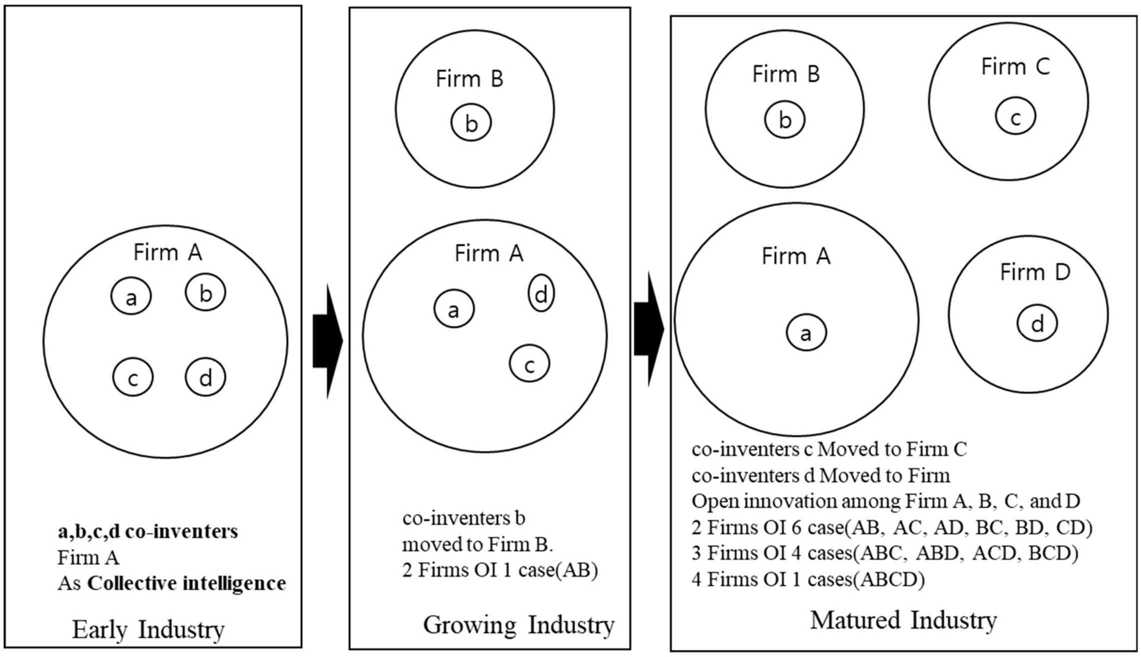

Figure 3. The increase in open innovation (OI) possibility by collective intelligence with the maturing of industry.

6. Conclusions

6.1. Implications: The Value of CL

CL has several effects, as illustrated in Figure 2. We identified the value of CL using a statistical analysis. However, the value of CL differs according to industry, which can be traced back to the growth stage of the industry or the accumulation level of CL.

At the invention stage of firms, CL can have several meanings. First, in this stage, CL increases the focal effects of the firm at the patent; second, CL can motivate communications in the firm and the development of new ideas for patents will be possible; third, CL can motivate open innovation of patents in firms in the future by moving people who had joined the patents as co-inventers from other firms. Therefore, firms to which co-inventors moved should have a willingness to collaborate with the patent of the original firm.

Firms in infant industry should not hesitate to invite more diverse inventers when they develop new technologies to motivate open innovation or technology transfer about the technology after growing up of the belonging industry.

Government should trigger collective intelligence in the invention steps to increase the commercialization of the technology with open innovation.

6.2. Limitations and Future Research Goals

In this study, we identified the role or value of CL during the invention stage. In this sense, we did not fully examine CL. We should perform a diverse case study to identify the key factors of CL at the firm level. We can identify the main factors of CL and the dynamics of CL through several case studies.

Second, additional statistical analyses to compare several industries at different growth levels to analyze the relationship between CL and OI are needed. The differences in CL according to the industrial life cycle and other factors, such as belonging to a sectoral innovation system, should also be investigated.

So to say, in additional industries with more diverse conditions, this research should be repeated to generalize the implication of this research.

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