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Article

The Crowdfunding Model, Collective Intelligence, and Open Innovation

Sangjae Pyo [1], Hyoung-Ryul Ma [1], Sumi Na [2] and Dong-Hoon Oh [1,]*

[1] Tech. Policy MD Group, Office of Strategic R&D Planning (OSP), Seoul 06152, Korea; classical@keit.re.kr (S.P.); designme@keit.re.kr (H.-R.M.)
[2] Global Startup and Venture Research Office, Korea SMEs & Startups Institute (KOSI), Seoul 07074, Korea; smna@kosi.re.kr
* Correspondence: hoon.oh@keit.re.kr

Abstract: In recent years, crowdfunding has attracted the attention of tech startups. It has become a good alternative way to readily raise funds, especially during the early startup stages. However, in the case of mass intelligence, it is quite difficult to ensure the accuracy and reliability of knowledge. Individual investors who are not experts in science and technology often face difficulties investing in technology companies. In this regard, a new type of collective intelligence formed by accredited professionals needs to be attempted. This paper explores an alternative crowdfunding model for enhancing access to technology investments by the general population through an investor acceptance model. We developed an investor acceptance model to examine how the crowdfunding model involving scientists and engineers is adopted by individual investors using survey data from the general population. The results revealed that individual investors have a positive attitude towards investing through the crowdfunding model when they perceive that the information provided by a group of scientific experts is useful. We found that the perceived usefulness of the information from scientists and engineers is affected by the perceived quality of the information and perceived credibility of the scientists and engineers. We also suggest a basic concept for the crowdfunding model utilizing the collective intelligence of scientists and engineers for tech startups. The results could suggest a policy direction for promoting innovation.

Keywords: startups; crowdfunding; investment; technology; scientists; engineers; collective intelligence; open innovation; individual investor; fund-raise

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1. Introduction

Access to finance is one of the most important factors in supporting the innovation process of startups toward the maturity phase [1]. However, due to the lack of information and the uncertainty of investment success, startups receive comparatively less investment than large enterprises [2]. Furthermore, corporate venture capital is more likely to invest in companies with potentially lower information costs [3].

In recent years, crowdfunding has emerged as a new way to finance businesses for which it is difficult to set up an investment fund because of their innovative character [2,4,5]. Crowdfunding is defined as "the practice of obtaining needed funding by soliciting contributions from a large number of people, especially from the online community", according to the Merriam-Webster dictionary [6]. Crowdfunding is a unique way of raising money promoted by an increasing number of internet sites [4]. Through crowdfunding platforms, consumers identify valuable investments according to their preferences and their favorite products [7]. Individual investors can also start investing small amounts in promising technologies, so it becomes easier for companies to raise funds. Entrepreneurs choose crowdfunding for capital collection and marketing effects [8]. According to a recent study, companies with successful crowdfunding show good economic performance and employment growth [9]. Crowdfunding also allows entrepreneurs to retain more control over their company than if they receive venture capital [10].

There are two key factors that increase the probability of success for a crowdfunding project. First, it is essential to better understand and predict customers' strategic behavior before designing a crowdfunding project. The project's success is affected by the sensitivity of the optimal expected profit, the success rate, and the risk concerning the fixed cost and the opportunity cost coefficient [11]. Second, digital storytelling matters in attracting funding investors. Digital storytelling provides better service and convenience for investors and significantly impacts their perception of performance expectations [12].

The knowledge and environment of investors influence investment behavior [13]. The signals of project quality have a significant positive effect on the investment decisions around crowdfunding for science and technology projects [14]. However, in the case of mass intelligence in technology, it is quite difficult to secure accurate and reliable knowledge. Since most individual investors are non-experts in science and technology, it is difficult for investors to invest in the technology sector. Whether a product is feasible in the market [15] and the existence of functional prototypes for the product are important factors in investment decisions [16]. Information asymmetry is a hindrance to individual investors' investment in technology. Crowdfunding is transparent for its users through the accumulated amount of pledges and the number of investors it involves. However, because quality information is asymmetrical, investors cannot fully understand each business [17]. In a recent study, we confirmed that information sharing helps reduce information asymmetry [18] and that the perceived trust and perceived risk jointly created by the platform and crowdfunding have a positive effect on participation intention [19]. Furthermore, it was confirmed that recognizing the value of communication with others through participation in crowdfunding could affect social interaction online [20].

To the best of our knowledge, there is little previous research on the impact of signals from experts on investors' behavior. Our paper focuses on a crowdfunding model involving scientists and engineers. Accredited professionals could offer signals that are useful in the reduction of information asymmetry for individual investors in the face of uncertainty in investment decision-making. In this study, we investigate how individual investors adopt the crowdfunding model involving scientists and engineers. The purpose of the study is to present a model that describes which factors affect the acceptance attitude of individual investors for this crowdfunding model and how they relate to each other. In addition, we suggest a process for the crowdfunding model that involves scientists and engineers. The findings will be able to provide fundamental data to policymakers by presenting specific processes of models as well as individual investor acceptance of a new model that could facilitate promising technology investments.

The outline of the paper is as follows. Section 2 includes the various theories that underlie this study; research into theories of technology adoption is introduced in this section. Section 3 describes the data, the methods used to test the hypotheses, and the research framework. Section 4 provides the results of the empirical analysis. Section 5 discusses the relationship between crowdfunding, collective intelligence, and open innovation. Section 6 concludes the paper.

2. Literature Reviews

2.1. Theoretical Framework

Adoption models are based on social psychology theories that deal with beliefs, attitudes, intentions, and behaviors. In terms of social psychology, research into factors that cause individual behavior has expanded, and it has begun to be applied to the study of the information technology acceptance process [21,22].

The Theory of Reasoned Action (TRA) was developed in 1975 by Fishbein and Azjen to predict human behavior under complete volitional control [23]. According to the TRA, attitudes toward behavior and subjective norms influence behavioral intention, leading to behavior such as [24]. The TRA is a valuable model for predicting consumer behavior and behavioral performance [25,26] and serves as the theoretical foundation for the Theory of Planned Behavior (TPB) and the Technology Acceptance Models (TAM) [27].

The TAM is a theory proposed by Fred Davis based on the TRA to explain and predict the acceptance of user behavior for information technology [28–30]. According to the TAM, the user's intention to use the system determines the actual use of the system, and the user's intent to use the system is influenced by the user's attitude toward using the system. Fred Davis presented two independent constructs of user acceptance: perceived usefulness and perceived ease of use concepts to illustrate user acceptance, which he described as influencing behavior. On the other hand, subjective norms were excluded from the TAM [24]. The TAM is widely used to focus on system utilization and reliable measurement tools that exist and is parsimonious and sufficiently empirically tested [31].

Fred Davis, who developed the TAM, proposed an extended technology acceptance model (TAM2) that included external factors affecting the information technology acceptance process at the organization level with Viswanath Venkatesh. Additional variables as determinants of perceived usefulness are subjective norms, image, job relevance, output quality, and result demonstrability. Additionally, additional variables as regulatory variables are experience and collegiality. Attitudes were excluded from the TAM2 to maintain the model's simplicity and increase the explanatory power of the willingness to use it [32]. Since then, the TAM3 was proposed, with conditioned variables of perceived ease (self-efficacy, external support perception, anxiety, playfulness) and regulatory variables (perceived pleasure, objective ease) [33].

Sussman and Siegal presented an integrated model based on the Elaboration Likelihood Model (ELM), which describes the acceptance of information [34]. They hypothesized that the provided argument quality and the source credibility would act as leading variables for the information usefulness. The information usefulness would again be the leading variable for determining information adoption. In addition to the concept of the ELM, they also hypothesized that when the argument quality or the source credibility affects the information usefulness, the expertise and immersion of information users will affect as context variables, and all of these hypotheses are empirically analyzed through surveys [34]. Hyoung-Yong Lee and Hyunchul Ahn empirically analyzed the user acceptance model for mass collective intelligence represented by Wikipedia. They proposed the behavior model based on Sussman and Siegal's research [34]. They conducted a survey and validated it through a PLS structural equation model [35].

User acceptance of new technologies and mass intelligence based on adoption theories has been widely investigated, but few have attempted to address collective intelligence formed by accredited professionals. To the best of our knowledge, this study is the first paper to investigate individual investors' acceptance of the crowdfunding model based upon the collective intelligence formed by scientists and engineers. Previous studies have investigated user acceptance for new technologies or systems. This paper presents not only user acceptance but also a process model of the crowdfunding platform to provide fundamental data to policymakers.

2.2. Hypotheses Development

Figure 1 below indicates the research model used in this study. This study draws on the work of Sussman and Siegal [34] to develop the theoretical framework for the analysis of the user acceptance model. It is extended to include various leading variables that can account for the intention to use the crowdfunding platform. The proposed model consists of a total of seven hypotheses.

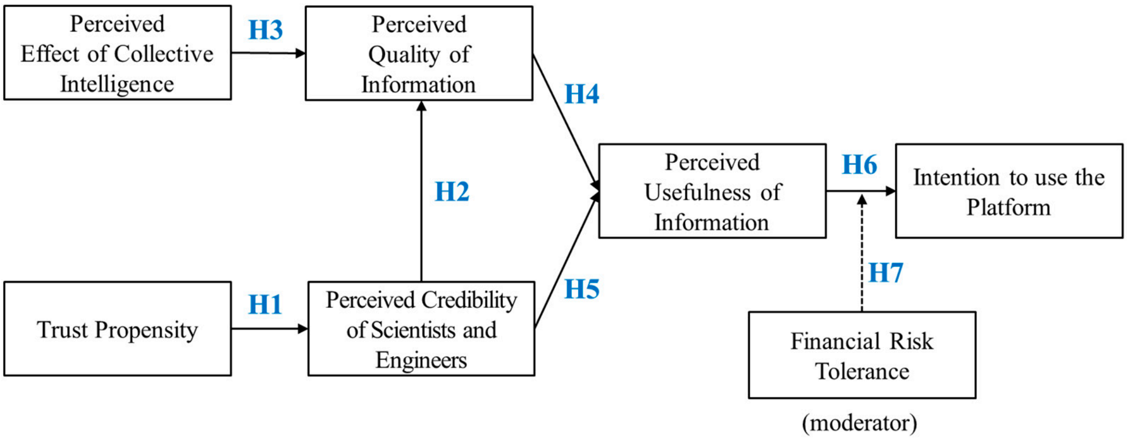

Figure 1. Research framework.

Individuals choose the most reasonable mode of action after comparing the benefits that may arise from a given set of decision options [36]. To reach the decision, trustworthiness perceptions and trust intentions depend on individual differences because the trustor relies on a worldview, cognitive bias, or heuristic [37]. According to Gene M. Alarcon et al., those higher in trust propensity tend to trust others [38]. For platforms where the information provided by experts has a significant impact, it can be thought that the basic level of trust the general public has in others could affect the confidence in the experts. All this considered, the first hypothesis of the study is postulated as:

Hypothesis 1 (H1). *Individual investors' trust propensity impacts their perceived credibility of scientists and engineers.*

Trust plays an important role in improving the functionality of all business operations in situations where there is risk and uncertainty [39]. Cooperation is an act in which individual goals contribute to each other, while trust is an expectation that the other will perform certain actions and a willingness to take risks and damages from the other's failure [40]. In sociology, trust is divided into parts of emotion and reason, and the former is defined as emotional trust and the latter as cognitive trust [41]. Cognitive trust positively coordinates the relationship between the quality of information and the operational performance of crowdfunding [42]. A system quality means desirable characteristics of information systems, such as ease of use and learning, flexibility, credibility, and sophistication. If investors have high confidence in scientists and engineers, they will recognize that the quality of the information provided by the platform involving scientists and engineers is also excellent [43]. Thus, the second hypothesis of the study is postulated as:

Hypothesis 2 (H2). *Individual investors' perceived credibility of scientists and engineers impacts their perceived quality of the information provided by scientists and engineers.*

Bonabeau argued that experts working together in groups, advising and critiquing, could create synergies rather than handling tasks individually, resulting in better solutions to the problem [44]. The quality of forecasts is significantly improved if independent expert judgments are aggregated rather than those predicted by individual experts [45]. Groups that collaborate organically also solve challenges faster and more accurately than others [46]. By the same token, the collective intelligence of scientists and engineers from various fields can provide information of higher quality than that provided by a single expert. Thus, the third hypothesis of the study is postulated as:

Hypothesis 3 (H3). *Individual investors' perceived effect of the collective intelligence of scientists and engineers impacts their perceived quality of the information provided by scientists and engineers.*

The quality of information affects the operational performance of crowdfunding [39]. The perceived information quality also has a negative impact on the perceived investment risk [47]. Sussman and Siegal examined how knowledge workers are affected by adopting advice they receive in mediated contexts and emphasized assessing the information's usefulness as a mediator in the information adoption process. They recognized argument quality as a central route, source credibility as a peripheral route, and information usefulness as a mediator. According to Sussman and Siegal's information adoption model, information adoption is determined by two leading variables, argument quality and source credibility [34]. In the context that Sussman and Siegal's findings would also be valid in mass intelligence of scientists and engineers, we derived two variables: perceived quality of information and perceived credibility of scientists and engineers as leading variables for the perceived usefulness of information [34]. Thus, the fourth and fifth hypothesis of the study are postulated as:

Hypothesis 4 (H4). *Individual investors' perceived quality of the information provided by scientists and engineers impacts their perceived usefulness of the information provided by scientists and engineers.*

Hypothesis 5 (H5). *Individual investors' perceived credibility of scientists and engineers impacts their perceived usefulness of the information provided by scientists and engineers.*

According to the technology acceptance model, the perceived usefulness of new technologies significantly impacts an individual's attitude toward using the system [29]. Based on the perspective of the technology acceptance model, the information formed by the mass intelligence of scientists and engineers can be interpreted in the same context. If investors consider the information provided by scientists and engineers as useful, they will actively accept it. Thus, the sixth hypothesis of the study is postulated as:

Hypothesis 6 (H6). *Individual investors' perceived usefulness of the information provided by scientists and engineers impacts their intention to use the crowdfunding platform.*

People generally do not like risk, but there is a difference in the degree to which they try to avoid or take risks depending on the individual in situations where risk and benefit exist simultaneously. Risk tolerance is a subjective perception of risk that means how much risk an individual can accommodate. John defined financial risk tolerance as the maximum amount of uncertainty that someone is willing to accept when making a financial decision, which reaches into almost every part of economic and social life [48]. Understanding an investor's financial risk tolerance is crucial in determining the applicability of an investment. People with high financial risk tolerance are likely to have a higher level of confidence investing in more risky assets and would behave differently [49]. Thus, the seventh hypothesis of the study is postulated as:

Hypothesis 7 (H7). *Individual investors' financial risk tolerance impacts the interaction between perceived usefulness of the information and intention to use the crowdfunding platform.*

3. Methodology

3.1. Data Collection and Sample

Drawing on an existing literature and research model, survey data are collected from a sample of respondents that took a survey. We manipulated each factor contained in the model into between three and four measurement tools, referring to existing literature, and developed measurement questions using the 7-point Likert-type scale ranging from "strongly disagree" (score 1) to "strongly agree" (score 7). The population of the study comprised people in various filed who subscribe to newsletters from Korea Evaluation Institute of Industrial Technology (KEIT), a public institution that plans, evaluates, and manages industrial technology R&D. A total of 518 people were finally used in this study. Table 1 below contains the demographics of the participants.

Table 1. Demographic information on subjects.

Variable	Classification	Frequency	Percent
Gender	Male	474	91.51%
	Female	44	8.49%
Ages	Between 20 and 29 years	4	0.78%
	Between 30 and 39 years	68	13.12%
	Between 40 and 49 years	149	28.76%
	Between 50 and 59 years	190	36.68%
	Older than 60 years	107	20.66%
Position	Research and Development	301	58.10%
	Engineering	58	11.20%
	R&D Policy Planning	48	9.27%
	Office Management	98	18.92%
	Other	13	2.51%
Occupation	Employee in University	64	12.36%
	Employee in Public Sector	89	17.18%
	Employee in Private Sector	351	67.76%
	Other	14	2.70%
Education	Ph.D.	199	38.42%
	Master's degree	153	29.54%
	Bachelor's degree	138	26.64%
	Other	28	5.40%
Major	Mechanical · Material	137	26.45%
	Electrical · Electronic	78	15.06%
	Information and Communication	67	12.93%
	Chemical	56	10.81%
	Biomedical	75	14.48%
	Energy Resource	24	4.63%
	Knowledge Service	35	6.76%
	Other	46	8.88%

(Note: Appendix A provides quantitative measures and indicators).

3.2. Data and Measurement

The reliability analysis of this study examined the homogeneous composition of questions for variables measurement by applying Cronbach's alpha, which represents internal consistency. The results are shown in Table 2 as follows. The results for reliability assessment demonstrate reliabilities (above 0.70 [50]) for all scales. We confirmed that all the questions about the latent variable had high consistency.

The validity is to examine whether the observation variable measured the latent variable properly. Table 2 below displays that all factor loadings are above 0.7, and the validity is statistically significant [51].

To analyze construct validity, we assessed convergent validity and discriminant validity. The value of the average variance extracted (AVE) should be higher than 0.5 to achieve convergent validity [51]. Table 2 above shows that convergent validity is established. Additionally, confidence interval for a coefficient ($\Phi \pm 2 \times$ standard error) should not include 1.0 to achieve discriminant validity. The results presented in Table 3 show all the factors that do not include 1.0. Thus, discriminant validity is established.

Table 2. The results for reliability analysis and convergent validity analysis.

Latent Variable	Observed Variable	Factor Loading	Cronbach's Alpha	AVE
Perceived Effect of Collective Intelligence	PE1	0.784	0.852	0.592
	PE2	0.789		
	PE3	0.747		
	PE4	0.757		
Perceived Quality of Information	PQ1	0.864	0.903	0.755
	PQ2	0.920		
	PQ3	0.829		
Perceived Usefulness of Information	PU1	0.761	0.868	0.700
	PU2	0.870		
	PU3	0.863		
Intention to use the Platform	IP1	0.940	0.966	0.905
	IP2	0.985		
	IP3	0.931		
Trust Propensity	TP1	0.811	0.786	0.577
	TP2	0.845		
	TP3	0.613		
Perceived Credibility of Scientists and Engineers	PC1	0.798	0.844	0.644
	PC2	0.745		
	PC3	0.875		

(Note: AVE = average variance extracted).

Table 3. The results for discriminant validity.

Path	Φ	S.E.	$\Phi - 2 \times$ SE	$\Phi + 2 \times$ SE
PE–PQ	0.774	0.024	0.726	0.822
PE–PU	0.792	0.024	0.744	0.840
PE–IP	0.678	0.028	0.622	0.734
PE–TP	0.508	0.041	0.426	0.590
PE–PC	0.680	0.032	0.616	0.744
PQ–PU	0.755	0.024	0.707	0.803
PQ–IP	0.615	0.030	0.555	0.675
PQ–TP	0.539	0.038	0.463	0.615
PQ–PC	0.735	0.026	0.683	0.787
PU–IP	0.788	0.020	0.748	0.828
PU–TP	0.606	0.036	0.534	0.678
PU–PC	0.744	0.027	0.690	0.798
IP–TP	0.520	0.037	0.446	0.594
IP–PC	0.587	0.033	0.521	0.653
TP–PC	0.749	0.028	0.693	0.805

(Note: Φ = correlation, S.E. = standard error).

The results for the goodness of fit test are presented in Table 4. Absolute fit measures present how well a theoretical model fits the sample data. We use root mean square of error approximation (RMSEA) and goodness of fit index (GFI) as absolute fit indices. Incremental fit indices indicate the relative improvement in the fit of the research model. We use comprehensive fit index (CFI), adjusted goodness of fit index (AGFI), and parsimony goodness of fit index (PGFI) as incremental fit indices. Parsimonious fit measures state indices that make it possible to examine the fit of competing models on a common basis. We use parsimonious normed fit index (PNFI) as parsimony fit indices. According to the results for the goodness of fit test, each index value satisfies its level of acceptance. Thus, the model fit is satisfactory.

Table 4. The results for the goodness of fit test.

Name of Category	Name of Index	Level of Acceptance	Index Value
Absolute fit indices	RMSEA	≤0.08 [52]	0.072
	GFI	≥0.8 [53]	0.905
Incremental fit indices	CFI	≥0.9 [54]	0.954
	AGFI	≥0.8 [55]	0.868
	PGFI	≥0.5 [56]	0.652
Parsimony fit indices	PNFI	≥0.5 [56]	0.752

4. Results

This study used Structural Equation Modeling for the statistical analysis. The internal consistencies of scale were assessed through computing Cronbach's Test. The construct validity was evaluated via convergent and discriminant validity. The results of testing the hypothesis using a structural equation model are presented in Figure 2 below. Findings show that all factors have a significant impact ($p < 0.001$). In support of H1, we found that trust propensity has a significant impact on the perceived credibility of scientists and engineers. The path coefficient between trust propensity and perceived credibility of scientists and engineers was the highest at 0.83. Additionally, the results indicate that the perceived quality of information is affected by the perceived credibility of scientists and engineers and the perceived effect of collective intelligence. Hence, H2 and H3 are also confirmed. The path coefficient (0.58) between perceived quality of information and perceived effect of collective intelligence was higher than those (0.36) of perceived quality of information and perceived credibility of scientists and engineers. This suggests that individual investors perceive the effect of collective intelligence formed through collaboration more than trust in a group of experts who are scientists and engineers. Accordingly, the crowdfunding platform needs to be designed with structures that facilitate collaboration among experts participating in the platform. In addition, it was confirmed that the perceived usefulness of information is affected by both perceived quality of information and perceived credibility of scientists and engineers with path coefficients of 0.53 and 0.36, respectively, at a significant level of 0.1%. Thus, H4 and H5 are supported. Among them, they were found to be more influenced by the perceived quality of information. This means that more resources and efforts must be put into improving the quality of the information provided to attract participation from individual investors in the crowdfunding platform. Further, we found that the intention to use the crowdfunding platform involving scientists and engineers is influenced by the perceived usefulness of the information. The path coefficient of 0.76 indicates a strong positive relationship. Thus, H6 is supported.

Lastly, we verified that the impact interaction between perceived usefulness of information and intention to use the crowdfunding platform is affected by financial risk tolerance. As a result, we confirmed that the perceived usefulness of the information and financial risk tolerance has a significant effect on the intention to use the platform (each of p-value = 0.000) and that the interaction between perceived usefulness of the information and financial risk tolerance also has a significant statistical impact (p-value = 0.012). This means that individual investors' attitudes toward the risk of investing in funds also affect their attitudes toward accepting the crowdfunding platform.

However, some might argue that systematic differences among subsamples can bias our result seriously. Thus, we checked systematic differences among groups by gender, educational background, and major, respectfully. The results revealed that there is no statistical difference at the 5% significance level.

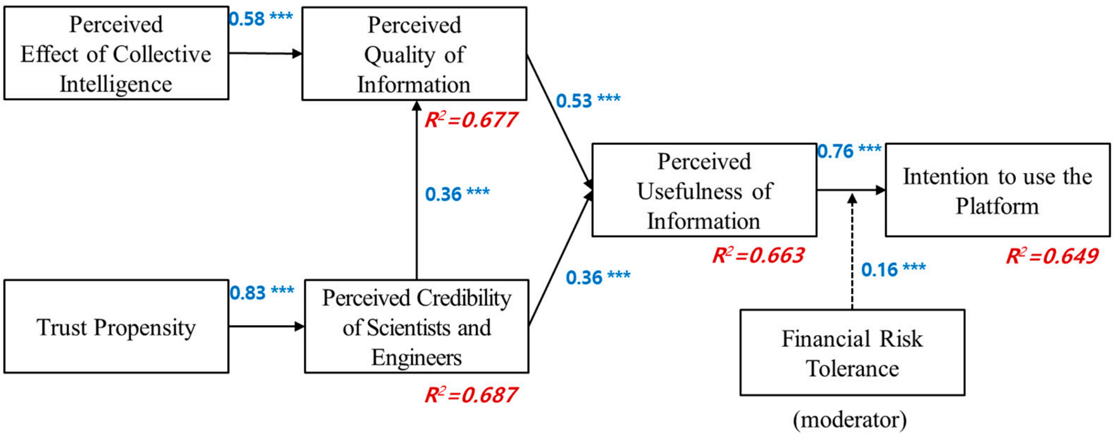

Figure 2. The results of a hypothesis testing. Note: *** $p < 0.001$.

5. Discussion

5.1. Crowdfunding and Collective Intelligence

We discuss two crowdfunding model ideas combined with the concept of collective intelligence as follows. The first idea is to combine collective intelligence with the conventional IP trust model. IP Trust Model is a way in which a trust company receives IP from an innovative company and raises funds based on it. A group of scientists and engineers can design an investment portfolio by selecting companies with excellent intellectual property (IP) using their expertise. Referring to the investment portfolio composed by scientists and engineers can help individuals make investment decisions through the crowdfunding platform.

The second idea is to combine collective intelligence with a Business Development Company (BDC). A company's selective waiver of intellectual property rights may benefit a company's business [57]. A BDC is an organization that invests money in privately owned small- and medium-sized companies and distressed companies. A management company can establish a BDC with scientists and engineers for each technology area, such as electric vehicles, robotics, and smart grid. Investors can invest in BDCs designed by scientists and engineers through the crowdfunding platform.

5.2. Crowdfunding, Collective Intelligence, and Open Innovation

As digitization progresses, the openness of information and technology has expanded, and the importance of open innovation is also emphasized [58–63]. Adopting existing external knowledge and technologies contributes to business growth [64–66]. Open innovation requires various tools and technologies to ensure quality, accuracy, and speed [67]. In the case of converted industry in a mature stage and emerging industry, an open innovation strategy focused on technology is useful [68]. The ability to capture value determines the success of open innovation [69].

According to JinHyo Joseph Yun's study, the more knowledge in an economic system, the more the motivation of open innovation by collective intelligence [70]. Additionally, leveraging collective intelligence techniques is potentially helpful in research and development [71]. We focus on collective intelligence formed from accredited experts in science and engineering. The proposed crowdfunding model could reduce asymmetry that negatively affects investment in firms through the collective intelligence of experts and promote open innovation by strengthening internal cooperation [72]. JinHyo Joseph Yun argues that collective intelligence can motivate open innovation in new companies by moving those who joined the patents as co-inventors [73]. In the same vein, scientists and engineers participating in the proposed crowdfunding model can generate innovations in their organizations or enterprises.

Crowdfunding also requires the joint participation of multiple stakeholders in innovative work [74]. In that sense, crowdfunding can play a role as innovation intermediaries that contribute to the success of entrepreneurial opportunities by supporting open innovation activities to facilitate the interaction and identification of collaboration opportunities [74–79]. To create a combination of entrepreneurs and technology and markets, it is necessary to provide and foster financial systems such as crowdfunding [80].

6. Conclusions

6.1. Implication

This paper tested an investor acceptance model of the crowdfunding platform involving scientists and engineers. We developed the research framework consisting of seven variables and validated it through a structural equation model based on the survey. The conclusion from this study is these: (1) the usefulness of information affects the intention to use the crowdfunding platform involving scientists and engineers. The perceived usefulness of information is determined by the perceived quality of information and the credibility of scientists and engineers. (2) The perceived effect of collective intelligence and the credibility of scientists and engineers affect the perceived quality of information, and trust propensity has a significant impact on the credibility of scientists and engineers. (3) The perceived quality of information affects the perceived usefulness of information more than the perceived credibility of scientists and engineers. The perceived effect of collective intelligence affects the perceived quality of information more than the credibility of scientists and engineers. Proceeding from these results, it is highly probable that the quality of the information they produce is more important than trust in scientists and engineers. (4) An individual's attitude toward financial risk influences the intention to use the crowdfunding platform. To sum this up, individual investors recognize that the information provided by scientists and engineers through the platform is high-quality, and they have confidence in scientists and engineers, so they recognize that the information provided by the crowdfunding platform involving scientists and engineers will be valuable and they will be willing to use the platform.

The academic significance of this study is as follows. This study presented the behavior model that explained individual investors' acceptance of the crowdfunding model and verified it through survey-based empirical analysis, while numerous studies applying the adoption theory mainly presented user acceptance models for new technologies or mass intelligence. The study emphasized how individual investors accept collective intelligence formed by accredited professionals. Furthermore, this study provides practical implications for policymakers in charge of technology financing policy and asset management companies. It will enhance the efficiency of policymaking by presenting the basic concept of the model to stakeholders, including policymakers, as well as individual investors' acceptance of the crowdfunding platform that can facilitate promising technology investments. The results of this study suggest that efforts should be made to improve the quality of the information provided by scientists and engineers to attract participation from individual investors in the crowdfunding platform. It is recommended that the platform be designed to ensure that the information provided by scientists and engineers is accurate, reliable, and consistent. Furthermore, the study suggests that encouraging collaboration between scientists and engineers can improve the quality of information.

6.2. Limits and Future Research Topic

Although this study offers academic contributions and practical implications, some limitations were recognized. First, the data were collected in South Korea only. In this regard, this study may not apply to other countries due to system and cultural differences. Cross-national comparative research would be vital for better research in the future. Second, the research framework of this study is not designed to include all possible variables. Additional variables need to be considered that describe the perceived quality of information and the perceived credibility of scientists and engineers to measure the behavior of individual investors in detail.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Quantitative Measures and Indicators

Perceived Effect of Collective Intelligence: four items adapted from Bonabeau [44].

1. I think it is more likely that information created through collaboration between several scientists and engineers on the crowdfunding platform is more reliable than information created by one scientist or engineer alone.
2. I think it is more likely that a group of experts from various fields will produce more meaningful information on the crowdfunding platform than a group of experts from one field.
3. I think providing information that tells you which fund the scientist was involved in would help the individual investors decide on investment.
4. I think that if the platform provides information on the investment status of each fund (such as the amount of investment, the number of investors, etc.), it can help judge the investment.

Perceived Quality of Information: three items adapted from Petter et al. [43].

1. I think that the scientists and engineers involved in the crowdfunding platform will provide accurate information about their area of expertise.
2. I believe that the scientists and engineers who participate in the crowdfunding platform will provide reliable information about their area of expertise.
3. I believe that the scientists and engineers involved in the crowdfunding platform will provide coherent information about their area of expertise.

Perceived Usefulness of Information: three items adapted from Davis [81].

1. I think we can quickly obtain the information we need to invest in technology from the crowdfunding platform.
2. I think the crowdfunding platform can increase my chances of successful investment.
3. I think the crowdfunding platform will make investing in technology easier.

Intention to use the Platform: three items adapted from Vankatesh et al. [33].

1. I am willing to use the crowdfunding platform.
2. I think I will use the crowdfunding platform.
3. I am planning to use the crowdfunding platform.

Trust Propensity: three items adapted from Gene et al. [38].

1. I think people generally care about others as well as themselves.
2. I think most people try to be honest with others.
3. I am not very suspicious of persons I first meet.

Credibility of Scientists and Engineers: three items adapted from Sussman et al. [34].

1. I think that the scientists and engineers involved in the crowdfunding platform will participate in good faith.
2. I think that the scientists and engineers involved in the crowdfunding platform will want investors to profit from their investment.
3. I believe that the scientists and engineers involved in the crowdfunding platform will provide the right knowledge.

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