Early-Stage Success Factors in R&D Collaborations

Author: Bill-Frederic Beba
University of Twente
P.O. Box 217, 7500AE Enschede
The Netherlands

ABSTRACT

Empirical studies on R&D collaborations between companies and universities laid emphasize on early stage factors enabling the success of such collaborations. This paper extends the current research by investigating the impact of two factors on the R&D collaboration success. The paper seeks to analysis if a narrow project breadth and complementary expertise lead to success in terms of product development success as well revenue generated by the R&D collaboration. The method of analysis includes a binary logistic regression. The logistic regression model is generally used to analyze the relationship between a single predictor, or multi-predictors, and an outcome that is dichotomous in nature (having 2 outcomes such as occurrence or absence of a certain ‘’event’’; in our case success or not successful. Results of data analyzed show that project breadth is an early stage success factors for R&D collaborations only in terms of product development. The result in this study showed that it wasn’t a success factor regarding the revenue generated by the R&D collaboration. In this study, complementary expertise also appears to not be an early stage success factors for R&D collaborations in regards to product development and revenue generated.

Graduation Committee members:

First supervisor: Igors Skute, MSc

Second supervisor: Dr. Isabella Hatak

Second examiner: Dr. Kasia Zalewska-Kurek

Keywords

Research & Development collaborations, success, project management, project scope, complementary expertise, technical expertise, product development, revenue, commercialization

9th IBA Bachelor Thesis Conference, July 5th, 2017, Enschede, The Netherlands.

1. Introduction

Research & development collaborations have been widely accepted as an important driver of firms' innovation performance. Nowadays, scientific breakthroughs and new technologies seem to generate tremendous value and spread in all fronts (Schwab, 2016). In this regard, Chesbrough (2003), Dahlander and Gann (2010), and Fey and Birkinshaw (2005) emphasize that collaborations generally can enhance the innovative performance of companies due to the fact that the companies can get access to complementary resources. Here, the project formation phase is an essential stage for the subsequent success potential of such strategic collaboration. In this phase, all elements are agreed among collaboration partner affecting the project throughout the collaboration. It is from importance to take into consideration the project breadth of a company. How narrow or wide is the breadth of the project the companies are working on. Other authors such as Clarke (1999) also mention several crucial elements for collaboration success: For example, collaboration partners need to be selected carefully in terms of complementary competence and mutual benefit in the project scope so that R&D collaborations pay off.

Although a lot of studies have been conducted on identifying success factors for R&D collaborations, insights on how we implement these factors are lacking. Dyer, Kale and Singh (2001) and Barnes, Pashby and Gibbons (2006) are stating that relatively little work has been done with reference to how this knowledge could be applied in practice to produce improvements in collaboration management. Hence, knowledge integration processes between several parties and their management issues need to be learned for future R&D collaborations. (Liyanage, Greenfield and Don, 1999). Evidence of the evaluation on the factors facilitating organizational learning and the appropriation of knowledge and competence developed over the course of a R&D collaboration is missing (Ingham and Mothe, 1998).
In this article, the aim is to focus on early stage factors that influence the success of R&D collaborations in terms of product developments and revenue generation. We investigate, in this research, two main factors: how the collective project scope setting (wide/narrow) and how the complementary expertise, the knowledge and know-how that each parties bring into the collaboration, can impact the success of R&D collaborations in the early-stage. Therefore, the two research question of this study are as follows: What is the impact of a detailed project scope on the R&D collaboration success in terms of product development and revenue generation. And what is the impact of the complementary expertise on the R&D collaboration success in terms of product development and revenue generation.

The empirical analysis draws on a data set of companies based in the Netherlands. By directly measuring the relationship between the success factors and the project success we can examine the likelihood of a research & development collaboration to succeed. Thus, it provides a better understanding of impactful early stage success factors for R&D collaborations.
The paper is divided into six different sections. Section 2 reviews the theoretical approaches found in the literature and identifies the research question and the hypotheses. Section 3 presents the research methodology and approaches used in the empirical analysis. Section 4 discusses the main results obtained during study. And finally, section 5 concludes and discusses the result of the main research.

2. Theory and hypotheses

2.1 Research and development collaborations

R&D collaborations are generally seen as pathways for process and product innovation. Asakawa (2010), states four specific types of collaborations: R&D collaborations with suppliers, competitors, and customers or with institutions (e.g. university). Generally, evaluating different criteria forms these types of collaborations. Firm Size, Type of industry the company operates in, degree of complementary expertise, are for instance some criteria that determines the likelihood to form R&D collaboration. This paper confronts all types of R&D collaborations and doesn't talk about a specific type of collaborations in particular. Collaboration is an impactful method that increases the quality of innovation and at the same time drives the industry forwards as whole. But what is the success in R&D collaborations? We can distinguish between two sorts of success the funding of the R&D project and the successful commercialization of the end product/service. Lim and Zain (1999) said that ''project success is normally thought of as the achievement of some pre-determined project goals'' (p.4). D'este and Perkmann (2011), also argue the fact that that collaborations are dominated by research-related motivations, such fund raising and learning from the industry and see the end commercialization as least important motivations. In order to investigate success, the perception of success is going to be defined by both the successful product development of the R&D collaboration and on the other hand by the successful end commercialization of the product/service from the R&D collaboration project.

2.2 Project scope and R&D success

Project planning is one, if not the most, important element in effective project management. It is the ground concept completing a project. Planning a project is complex; it requires a lot of time and organizational efforts in order to make things right/they way they should go. During the project planning the company have to think about all elements that need to be included in the project. Project planning consists of the project scope along with the project schedules and time frames in which the different activities/project should be done. 'Without a well-defined scope, the objectives of information system development can be vague and people may start to lose sight of what they are trying to develop' (Clarke, 1999, p.75). Chen, Law and Yang (2009), found out that poor scope definition negatively correlates to project performance. They state that the final project costs tend to be higher due to the inadequate project breadth. The wrong breadth will interrupt the project rhythm, increase the project time, and lower the productivity as well as the morale of the fieldwork. The wider the project scope (=breadth), the less focus on the particular project as the individual partner involvement is too low, with specialization however being necessary for success, etc. and the more narrow the scope (=depth), the more knowledge can be flexibly and speedy shared between the partners, with flexibility being critical for innovation (Zhou & Wu, 2010). Project Scope Management ensures that the project includes all the work required to complete the project successfully. Ward (1995) stated that scope and objectives are the guiding principles that direct the efforts of the project team. They determine a project's success or failure. Hence, project scope management is a key factor for collaborations and needs to be planned accordingly. Therefore, this would also suggest that project scope/breadth has a positive relationship with R&D collaboration success.

Hypothesis 1a: A narrow project scope (breadth) is positively related to products developed by the R&D collaboration projects.

Hypothesis 1b: A narrow project scope (breadth) is positively related the revenue generated by the R&D collaboration projects.

2.3 Complementary expertise and R&D success

In any field, there is a technical level of work that requires specialized knowledge and skill to generate success. The technical level of work can be learned through education, experience, or both. With regard to the collaboration context, complementary expertise is the level of knowledge/experience/skill that a partner has on a particular field, which the other partner lacks. Selecting the right partner, with the complementary expertise, is one of the most difficult and important factors before entering a R&D collaboration. The partner selection process should be done with regard to the long-term views of interest in the project and partner attractiveness (Dodgson, 1993). New opportunities and access to new knowledge are key drivers for collaboration search. Thus, organizations' skill-sets and know-how need to be complementary to benefit from the collaboration. Nesta and Saviotti (2005) empirically revealed that it is important for companies to collaborate with companies with a related or relative similar knowledge base. By doing so, both companies mutually benefit of the economy of scope of their complementary expertise. In fact, Knoben and Oelremans (2006) argued that similar expertise may result in a 'technological lock-in' in a way that nobody in the collaboration is going to profit from the 'complementary expertise as both companies offer each other too similar expertise. Too similar expertise closes the window for new opportunities and slows down future developments. Sakakibara (1997) found out by analyzing Japanese firms motivation to participate in government-sponsored R&D, that obtaining complementary knowledge and sharing specialized skills is the most important objective. Brockhoff et al. (1991) found similar findings in Germany. He found out that the possibility of capturing synergistic gains from the exchange of complementary technical knowledge is the one of the most important in R&D collaborations. Hence, complementary expertise is crucial and needs to be selected carefully as to similar or to diversified expertise, both results in the same low innovative performance.

According to the literature, it is possible to state that there is a positive relationship between complementary expertise and R&D collaboration success.

Hypothesis 2a: Complementary expertise is positively related to the products developed by R&D collaboration projects.

Hypothesis 2b: Complementary expertise is positively related to the revenue generated by the R&D collaboration..

3. Methodology

3.1 Research data set

Our analysis focuses on research and development collaboration. The data will allow us to explore the relations and links between the independent variables (project scope and complementary expertise) and the dependent variables, the revenue generated by the R&D collaboration as well as the successful product development. This will help us to determine the impact of the project scope/breadth and complementary expertise on the early success of the research & collaboration project. The Data used for this research paper is based on the larger dataset of collaborative high-tech research projects, funded by the NWO Domain Applied and Engineering Sciences (TTW, previously Technology Foundation STW), based in the Netherlands. NWO "connects people and resources to develop technology with added economic value that contributes to solving societal issues. This is realised through the funding of excellent applied and engineering sciences research, by bringing users and researchers together, and by supervising projects towards optimal opportunities for knowledge transfer" (NWO website, 2017). The dataset includes a total of 75 projects.

The dataset used for this research paper includes the leading technical Dutch universities and their spin-offs, selected research institutes and tech companies, such as Philips, DSM, TNO etc. The project participants involved in these joint research projects are researchers and scientists, both from academic and industry, as well as, the potential users of the results who are not a part of the corresponding research group (von Raesfeld, Geurts, Jansen, et al., 2012).

The time period of these collaborative research projects is between 2000 and 2004, thus it provides sufficient period to estimate the collaborative research results, in terms of generated revenue stream and degree of product development. Additionally, applied database was checked for errors and inconsistencies to detect duplicate or misspelled organisation entries.

3.2 Variables

3.2.1. Dependent variable

We are interested in seeing if the factors (project scope and complementary expertise) lead to early success in an R&D collaboration and thus if there is a revenue for the R&D collaboration. Our dependent variable will be measured by the actual revenue generated in the R&D collaboration project, the dependent variable takes the value of 1, if the joint collaboration process generated non-continuous or continuous revenue streams and the value 0 in case that the joint collaboration process didn't generate revenue.

In order to obtain complementary results, we decided to include another dependent variable in our analysis: product development results. This variable measures whether the R&D collaboration projects lead to a successful product development, that is whether it has been a success or not in terms of degree of developed product prototype or a product ready for the market. This second dependent variable is also a binary variable. This variable takes the value 1 if the R&D collaboration product development succeeded and led to a tangible prototype and/or product version ready for market, and takes the value 0 if no product was generated as result of the R&D collaboration project.

3.2.2. Independent variables

The independent variables are main elements of a research and development project, project scope/breadth and complementary expertise. We are going to analyze the significance of the relationship of these independent variables regarding our dependent variable.

In order to operationalize the first independent variable, we need to understand the project breadth of the companies, the analysis, based on the individual partner participation in other projects is to calculate an average score of projects for each separate project participant. Thus, for example, project A has 3 partners involved in the project: AKZO Nobel, Nutreco Nederland B.V., and RIKILT-Instituut voor Voedselveiligheid. Nutreco Nederland B.V., and RIKILT-Instituut voor Voedselveiligheid besides this project are not involved in other projects, while AKZO Nobel is involved in 8 other projects. Based on this input, the average score for the project is (1 + 1 + 8)/3 = 3.333'. This number, 3.33', is the project breadth score for the project. The cut-off value is 5. Meaning that all scores above 5 are stating high engagement in several projects and thus high project breadth. Below 5, we can observe low engagement and thus low project breadth.

To operationalize the second independent variables we attribute values (0 or 1) to the outcomes. 1 would be a positive match and 0 would not be a match. The second independent variable complementary expertise, we are analysing matches between partners within the same R&D project. We attribute 1 to the companies operating in a different sector and 0 if more than half of the companies within the project operate in the same sector.

The partnering breadth describes the extent to which firms and its partners are interdependent across the R&D project value chain (Oxley and Sampson, 2004; Li et al., 2012).

Mishra et al. (2015), claim that the R&D project value chain can be broadly categorized into different stages namely, planning and execution stage. Hence the concept of breadth covers the extent to which the R&D collaboration partners are involved across these distinct stages.

The coordination of partner involvement in an R&D project is a complex and interdependent process that requires continuous synchronization of actions and decisions between the collaborating firms (Reuer et al, 2002).

Considering Oxley and Sampson (2004) partnering breadth can be either high or low. Low partnering breadth describes the situation where the partners are only involved in the planning stage, but not in the execution stage. High partnering breadth would then be if the partner(s) were involved in every stage, planning and execution. In any field, there is a technical level of work that requires specialized knowledge and skill. It can be learned through education, experience, or both. Complementary expertise is the level of knowledge/experience/skill that a company or a person has on a particular field. However, to generalize it in this paper we are going to talk more about general involvement (project breadth) rather then going into detail on the planning and execution stages. Hence, low project breadth comes from high involvement to just one or very few R&D projects. On the other hand, low involvement results in lower project breadth, as the companies prefer to spread their attention to all their activities rather than committing all their efforts on fewer/only one project.

3.2.3 Control variables

Control variables may be related to the dependent variable. During the regression they are hold constant in order to investigate the relative relationship of the dependent variable and independent variable. The analysis is going to contain one control variable namely, number of participants per project. This will enable us see the correlation between the size of the R&D collaboration and the chances of a successful R&D collaboration project. The number of participants per project might be related to the availability of resources within the R&D collaborations or simply the joint competencies, as more participants might be involved in a project than in another.

3.2.4 Analysis

In order to test the hypotheses and determine if the chosen variables are indeed early stage success factors for R&D collaboration we need to make use of the right analysis method. In our case, a binary logistic regression was applied (Tables 1 – 3). In 1958, a statistician called David Cox developed the logistic regression. The binary logistic model he developed was used to estimate the probability of a binary response based on one or more predictor or independent variables (Cox, 1958).

Even though the logistic regression originally is from the nineteenth century (Cramer, 2002), the logistic regression has become more popular and has been increasingly employed over the years (Oommen, Baise, & Vogel, 2011).

The logistic regression model is generally used to analyse the relationship between a single predictor, or multi-predictors, and an outcome that is dichotomous in nature (having 2 outcomes such as occurrence or absence of an certain ''event'', where it can take only two values, ''0'' and ''1'', which represents the outcome occurrence/absence (Hosmer & Lemeshow, 2000).

As already mentioned above the main reason why logistic regression models are used is to predict dichotomous outcomes (e.g.: success/nonsuccess). Additionally, many of our dependent variables of interest are well suited for dichotomous analysis Ketih, W., Gamboa, B., (2016). Another benefit from the logistic regression analysis is that it is also used in combination with software packages like SPSS, SAS, to help to extend the analysis (Burns et al., 2008; Muijs, 2010).

4. Results

Some aspects of the descriptive statistics are worth mentioning. First of all, we can observe from the correlation table (Appendix 1) that the revenue score and the product score have a significant relationship and are relatively low to medium correlated, which means that success of a project in terms of revenue generated is partially linked to the successful product development within the R&D collaboration project. Second, product score has a significantly relationship with project scope, even though they have a low negative correlation. Third, the number of participants per project doesn't have a significant relationship with the success of R&D collaboration (whether it is product development success or commercialization), and a low correlation to our independent variables, project scope/breadth and complementary expertise. Hence, the control variable doesn't have a significant impact on the analysis.

Hypothesis 1A and 1B examine if project scope/breadth predicts the successful development of a product as well the successful end commercialization of the product generated within the R&D collaboration. If we take a look at the two tables (Table 2 and 3), we can observe that the project scope/breadth has no significant relationship to generating revenue within the R&D collaboration (See table 2). The p value for project scope/breadth in relation to generating revenue is = 0.915. 0.915 is greater than 0.05, therefore we can say that the variable is statistically not significant in predicting revenue generation for R&D collaboration projects. Hence we have enough evidence to statistically reject the hypothesis 1B. However, if we look at the relationship from project scope/breadth to product development success, we can see that the relationship is significant. The beta of the variable is -0.224 and the p value is equal to 0.039. 0.039 is lower than 0.05, therefore we can conclude that the variable Project scope/breadth has a negative statistically significant relationship to the successful development of products within the R&D collaboration project. Thus, hypothesis 1A is accepted. If we take a look at the exponential beta's for the project breadth in relation to the product score we can see that for every point increase in the project breadth their odd of creating a successful product within the R&D collaboration decrease by 0.8 times (Appendix 4). Therefore, we can deduce that the narrower the project breadth is within the R&D collaboration the more likely it is that this R&D collaboration is going to result in successful product development.

By looking at our two last hypotheses 2A and 2B we are investigating if complementary expertise is predicting product development success and commercialization success. We can see that in both cases, complementary expertise is not a significant predictor for product development success or commercial success. The p value in both cases is 0.904 for product development and 0.828 for successful commercialization; both these values are fairly high and are over the significance level 0.05. Correspondingly the estimates of their coefficients on the logit scale are relatively close to zero, which translate into odds ratios close to 1. The message seems to be that controlling for the other variables in the model there isn't any significant relationship between complementary expertise and product development success and commercial success. Therefore, both hypothesis 2A and 2B can be rejected.

Table 1
Range, Mean, Standard deviation and correlations of the variables (N=75).

	Range	Mean	S.D.	1	2	3	4	5
Revenue Score	0-1	0.240	0.430	1				
Prodcut Score	0-1	0.707	0.458	0.362**	1			
Project Scope	0-11.5	4.618	2.506	-0.026	-0.257*	1		
Complementary Expertise	0-1	0.480	0.503	-0.040*	-0.026	0.120	1	
Number of participants per project	0-11	5.400	2.493	0.149	0.104	-0.085	-0.112	1
N of cases 75								

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 2
Determinants of: Revenue genrated by R&D collaborations projects (N=75).

	1		2		3		4	
	B	s.e	B	s.e	B	s.e	B	s.e
Constant	-1.908	0.673	-1.845	0.888	-1.960	0.717	-1.898	0.923
Number of Participants per project	0.135	0.106	0.134	0.107	0.133	0.107	0.131	0.107
Project Scope			-0.120	0.114			-0.012	0.114
Complementary Expertise					0.121	0.552	0.120	0.552

Table 3
Determinants of: Successfull Product development in the R&D collaboration project (N=75).

	5		6		7		8	
	B	s.e	B	s.e	B	s.e	B	s.e
Constant	0.367	0.614	1.551	0.875	0.345	0.642	1.528	0.896
Number of Participants per project	0.970	0.108	0.080	0.114	0.960	0.109	0.780	0.114
Project Scope			-0.224*	0.109			-0.224*	0.109
Complementary Expertise					0.059	0.514	0.064	0.532

*. Correlation is significant at the 0.05 level (2-tailed).

5. Discussion and conclusions

The current study aims to contribute to the existing research by identifying early stage success factors for R&D collaborations. The study investigates the success of R&D collaborations in two different perspectives. On the one hand, it explores how the project scope/breadth and the complementary expertise may have a positive influence on the commercialization of the end product/service of the R&D collaboration. Meaning, if the R&D collaboration is generating revenue through the project. And on the other hand, it explores how the project scope/breadth and the complementary expertise may have a positive influence on the successful product development within the R&D collaboration project. Meaning that, the analysis looks if the R&D collaboration project resulted in a completed end product, in terms of development success whether the product has been commercialized or not. Building upon the specific data sample, this paper makes the following contributions. In this study, with this dataset, the results shows that the complementary expertise might not be an early stage success factor for R&D collaborations. Even thought this study didn't found complementary expertise to play a significant role in R&D collaboration success, it is not a reason to believe complementary expertise will never play an important role in R&D collaborations. Especially looking at our sample, we collected information on projects based in a relative small country, the Netherlands. Moreover, we saw from our data that all the R&D collaboration projects analyzed in this study belong to natural science sector. Hence, it would be interesting to analyze R&D collaboration across countries, due to the fact that other countries might have access to other technologies and thus could deliver complementary expertise. Ultimately, the relationship between the project breadth and product development success is an inverted U-shape curve, meaning that you are more likely to create a product on the extremes. From this study we even saw that it is even more likely for the R&D collaboration to successfully develop a product when the collaboration has a narrow range. In general, it seems logical, the narrower your project breadth is, the more focused the individual companies are going to be on the project the collaboration is working on. On the other hand, the wider your project breadth is, the less focused the companies are going to be on the project. Hence, the chances of developing a successful product are likelier with a narrow project breadth. With regards to the relationship between the project breadth and product development success represented as an inverted U-shape curve, it might seem that project breadth correlates with company size. Smaller companies generally have fewer projects than bigger companies; hence their project breadth is narrower. Taking to account the result of our study, the chances for smaller companies to have a successful product development are higher as their project breadth is narrower. Slowly the companies are getting bigger the more the U-shape curve comes to its central low point. At this point companies of relative medium size struggle to give the same quantity and quality of attention to every of their R&D collaboration project. This is due to the lack of necessary resources within the company as well as internal managerial issues. At this point of the curve, the likelihood of successful product development is the lowest. Nevertheless, such issues can happen to every company small, medium or big. However, the curve goes back up to finish it U-shape as big companies actually do have the necessary resource to cover the attention of all their R&D collaboration projects. Thus, bigger companies could narrow their project breadth on the individual R&D projects as they have the necessary resources to do so. Despite the fact, big companies, such as multi-national companies, might not always want to spend all their energy equally over the different R&D projects, as some probably seem to be more value adding in the short term. Therefore, the majority of the focus is going to switch on those projects while keeping the other projects running as low priority (low pace) in the background. This study finds that in terms of revenue generated from the R&D collaboration project, project scope is not a success factor. However, narrow project scope demonstrates that it is an early stage success factor for R&D collaboration of developing a product/prototype as outcome.

By taking a closer look at the model summaries (see Appendix 2 and 3). We can observe that the overall revenue score is lower than the product score. This shows that most of the R&D collaboration didn't generate revenue through the project. However, it also shows that despite the fact that the R&D collaborations weren't able to commercialize the product, 53 out of 75 projects, or 70.7% of them were able to successfully develop a product (see Appendix 3). Hence, the collaboration was a success in the pure scientific way of creating a working product. Interesting is that although so many of the R&D collaboration succeeded to develop a product only 18 out of the 53, meaning only a third of them were able to commercialize it. Clayton (1997) argues that the dilemma in managing disruptive technology in the heat of the battle is that nothing went wrong inside these companies (Clayton, 1997, pp. 73). This could tell us that within R&D collaboration the products may could have been commercialized but external factors might have interrupted it. Perhaps the market demand for such technology was not satisfied. Perhaps the companies misjudged the need or potential benefits of their technologies or perhaps potential clients did not recognize the potential benefits/advantages of this new technology or it simply did not meet their needs.

Another perspective of the literature argues that most collaborations are generally unstable and often lead to dissatisfactory results (Porter, 1987; Kogut, 1988; Reuer and Zollo, 2005). In Reuer and Zollo's study, only 15% of the completed R&D collaborations sampled were seen as successful. Another study from Kogut (1989) shows that about the half of the collaborations he sampled end up being a failure.

In recent years European research institutions aimed to improve R&D collaborations and the implementation of research results and their uptake by companies by setting up knowledge transfer offices. The European Commission believes that most of the success depends on the skills and competencies of the workers, including factors such as managerial autonomy and strategic roles assigned to them (European Commission, 2007). Additionally, the European Commission claims that the staff working on knowledge transfer must possess a variety of skills in order to carry out the tasks effectively (European Commission, 2007, pp. 7). It is important to create conditions for successful knowledge transfer. When a company and a university come into collaboration they can become a powerful driver of innovation and economic growth. The Silicon Valley for instance is a great example showing the success of long-running collaborations introducing new technologies at an incredible pace while modernizing the role of universities (Science Business Innovation Board, 2012). This can be possible through interaction and communication. D'este and Patel, 2007, as well as Perkmann and Walsh, 2007, made studies on knowledge and technology transfer that argues the numerous university-industry interactions that contribute to the diffusion. However, it seems that the challenge of knowledge transfer and how to prepare their staff working within the R&D collaborations has not been widely researched.

The paper also presents several different limitations in the study that may be able to serve as insight for future researches. The data sample used in the study-contained information about R&D collaboration projects only based in the Netherlands. Next, all the R&D collaboration projects analyzed in this study belong to natural science sector. Hence, future studies could add more variety in the specific domains from which each R&D collaboration project is coming from. Finally, the R&D collaboration projects were all based in the years 2000 to 2004, which aren't the most up to date R&D collaborations. It would be interesting for future research to see how collaboration projects might perform nowadays with the help of new and more advanced technologies.

Appendix

Appendix 1: Correlation table between the variables

Correlations

		Revenue Score	Product Score	Project Scope	Technology Complementarity	NumberofParticipants
Revenue Score	Pearson Correlation	1	.362**	-.026	-.040	.149
	Sig. (2-tailed)		.001	.826	.733	.203
	N	75	75	75	75	75
Product Score	Pearson Correlation	.362**	1	-.257*	-.026	.104
	Sig. (2-tailed)	.001		.026	.826	.374
	N	75	75	75	75	75
Project Scope	Pearson Correlation	-.026	-.257*	1	.012	-.085
	Sig. (2-tailed)	.826	.026		.915	.468
	N	75	75	75	75	75
Technology Complementarity	Pearson Correlation	-.040	-.026	.012	1	-.112
	Sig. (2-tailed)	.733	.826	.915		.338
	N	75	75	75	75	75
NumberofParticipants	Pearson Correlation	.149	.104	-.085	-.112	1
	Sig. (2-tailed)	.203	.374	.468	.338	
	N	75	75	75	75	75

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 2: Model Summary for dependent variable 1 (Revenue Score)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	81.008[a]	.022	.033

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a,b]

	Observed		Predicted: Revenue Score .0	Predicted: Revenue Score 1.0	Predicted: Percentage Correct
Step 0	Revenue Score	.0	19	0	100.0
		1.0	9	0	.0
	Overall Percentage				67.9

a. Constant is included in the model.

b. The cut value is .500

Appendix 3: Model Summary for dependent variable 2 (Product Score)

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	85.276[a]	.071	.101

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a,b]

	Observed		Predicted: Product Score .0	Predicted: Product Score 1.0	Predicted: Percentage Correct
Step 0	Product Score	.0	0	22	.0
		1.0	0	53	100.0
	Overall Percentage				70.7

a. Constant is included in the model.

b. The cut value is .500

Appendix 4: Regression table (Product score)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	ProjectScope	-.224	.109	4.265	1	.039	.799
	TechnologyComplementarity(1)	.064	.532	.015	1	.904	1.066
	NumberofParticipants	.078	.114	.463	1	.496	1.081
	Constant	1.528	.896	2.909	1	.088	4.608

a. Variable(s) entered on step 1: ProjectScope, TechnologyComplementarity, NumberofParticipants.

Appendix 5: Regression table (Revenue score)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	ProjectScope	-.012	.114	.011	1	.915	.988
	TechnologyComplementarity(1)	.120	.552	.047	1	.828	1.128
	NumberofParticipants	.131	.107	1.506	1	.220	1.140
	Constant	-1.898	.923	4.227	1	.040	.150

a. Variable(s) entered on step 1: ProjectScope, TechnologyComplementarity, NumberofParticipants.

References

Agarwal, N. & Rathod, U. 2006, Defining success for software projects: An exploratory revelation, International Journal of Project Management, Vol. 24, pp. 358–370

Arza, V., and Lopez, A., 2011, Firms' linkages with public research organisations in Argentina: drivers, perceptions and behaviours. Technovation, 10.1016

Asakawa, K., Cuervo-Cazurra, A., Un, A., 2011, Collaborations and Product Innovation. Product development & management association, 27: pp. 673–689.

Avison, D. E., and Torkzadeh, G. (2009): Information Systems Project Management, Sage Publications, Inc., pp. 87 -93.

Boardman, P.C., Pronomariov, B.L., 2009, University researchers working with private companies. Vol 29, pp. 142.

Brockhoff et al, 1991, Inter-firm R&D co-operation in Germany. Technovation 11, pp.142-153.

Burns, R. B., Burns, R., & Burns, R. P. (2008). Business research methods and statistics using SPSS. London: Sage

Chen C.C., Law C. H., and Yang S.C, 2009, Managing ERP Implementation Failure: A Project Management Perspective, IEEE Transactions on Engineering Management, Vol 56, No. 1

Chesbrough, H.W. (2003), Open Innovation: The new imperative for creating and profiting from technology. Boston, MA.: Harvard Business School Press.

Clarke A., 1999, A Practical use of key success factors to improve the effectiveness of project management, International Journal of Project Management, Vol 17, pp. 139-145.

Clayton M. Christensen, 1997. The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail. Boston, MA: Harvard Business School Press.

Cramer, J. S. (2002). The origins of logistic regression. Tinbergen Institute Discussion Papers, 02-119/4. Tinbergen Institute

Cox DR (1958). The regression analysis of binary sequences (with discussion) , J Roy Stat Soc B, 20: 215-242.

Dahlander, L ., & Gann, D.M. (2010). How open is innovation? Research Policy, 39(6), 699-709. Das T. K. & Teng, B. S. (2000). Instabilities of strategic alliances: an internal tensions perspective organization Science, 11(1), pp. 77-101.

D'Este, P., Pate P., 2007, University-industry linkages in the UK: What are the factors underlying the variety of interactions with industry? Pp. 1295-1313.

D'este and Perkmann, 2011, Academic engagement and commercialization: A Review of the literature on university-industry relations, Volume 42, Issue 2, Pages 423-442.

Dodgson, M., 1993, Technological collaboration in industry: strategy, policy and internationalization in innovation. London: Routledge, pp. 154-195.

Dyer, J.H. and Nobeoka, K., 2000. Creating and managing a high-performance knowledge-sharing network: the Toyota case. Strategic Management Journal, 21(3), pp. 345–395.

European Commission EUR 22836, 2007, Improving knowledge transfer between research institutions and industry across Europe: embracing open innovation. ISBN 978-92-79-05521-8

Fey, C.F., & Birkinshaw, J. (2005). External sources of knowledge, governance mode, and R&D performance. Journal of Management, 31(4), pp. 597-621.

Hosmer, D. W., & Lemeshow, S. (2000). Applied logistic regression. New York: John Wiley & Sons

Ingham, M. and Mothe, C., 1998. How to learn in R&D partnerships? R and D Management, 28(4), pp.249–261.

Ketih, W., Gamboa, B., (2016). Using Logistic Regression: A Case Study Impact of Course Length and Use as a Predictor of Course Success

Knoben and Oelremans, 2006, Proximity and inter-organizational collaboration: A literature review. International Journal of Management Review 8, pp. 71-89.

Kogut, B., 1988. A study of the life-cycle of joint ventures. In: Contractor, F.J., Lorange, P. (Eds.), Cooperative Strategies in International Business, Lexington. MA and Heath, Lexington, Toronto, pp. 169–185.

Li, D., Eden, L., Hitt, M.A., Ireland, R.D., Garrett, R.P. (2012), Governance in multilateral R&D Alliances. Organization Science.

Lim C.S., Zain M., 1999, Criteria of project success: an exploratory re-examination, International Journal of Project Management Vol. 17, No. 4, pp. 243±248.

Littler D., Leverick F., Bruce M., 1995, Factors affecting the process of collaborative product development: A study of UK manufacturers of information and communications technology products. Product Innovat Manage, 12 pp. 16–32.

Liyanage, S., Greenfield, P.F. and Don, R., 1999. Towards a fourth generation R&D management model-research networks in knowledge management, International Journal of Technology Management, 18(3/4), pp.391.

Mishra, A., Chandrasekaran, A., MAcCormack, A. (2015). Collaboration in Multi-Partner R&D Projects: The Impact of Partnering Scale and Scope. Journal of Operations Management. Volumes 33-34. Pp. 1-14

Muijs, D. (2010). Doing quantitative research in education with SPSS. London: Sage.

Mulcahy, R. (2009) ''PMP Exam Prep: Rita's course in a book for passing PMP exam'' sixth Edition, RMC publications.

Nesta, L., Saviotti, P.P., 2005. Coherence of the knowledge base and the firm's innovative performance: evidence from the U.S. pharmaceutical industry. Journal of Industrial Economics 54. Pp. 122-143.

Oommen, T., Baise, L. G., & Vogel, R. M. (2011). Sampling bias and class imbalance in Maximum-likelihood Logistic Regression. Mathematical Geoscience, 43, 99–120

Oxley, J.E., Sampson, R.C. (2004), The scope and governance of international R&D alliances. Strategic Management Journal, 25 (8-9), pp. 723-750.

Perkmann, M, Walsh, K., 2007, University-industry relationship and open innovation: towards a research agenda. International Journal of Mangement Reviews, 9 (4), pp. 259-281.

Porter, M., 1987. From competitive strategy to cooperative strategy. Harvard Business Review 65 (3), pp. 43–59.

Project Management Institute. 2000, A Guide to the Project Management Body of Knowledge, PMBOK Guide 2000 edition, Project Management Institute, Pennsylvania. pp.105.

PMBOK 2013: Guide to the Project Management Body of Knowledge (PMBOK Guide) - Fifth Edition

Reuer, J., Zollo, M., 2005. Termination outcomes of research alliances. Research Policy 34 (1), pp. 101–115.

Reuer, J.J., Zollo, M., Singh, H., 2002, Post-formation dynamics in strategic alliances. Strategic Management Journal, 23 pp.135-151

Sakakibara, M., 1997, Evaluating government-sponsored R & D consortia in Japan: Who benefits and how? Research Policy 26, pp. 447-473.

Schwab, K., 2016, The Fourth Industrial Revolution, World Economic Forum, pp.14-28.

Science Business Innovation Board, 2012, Making Industry-University partnerships work.

Von Raesfeld, A., Geurts, P., Jansen, M., Boshuizen, J., & Luttge, R. (2012). Influence of partner diversity on collaborative public R&D project outcomes: A study of application and commercialization of nanotechnologies in the Netherlands. *Technovation*, *32*(3), pp. 227-233.

Ward, J. A. 1995, Project pitfalls, Information System Management, Vol. 12, No. 1, pp. 74-76.

Zhou, K. Z. and Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. Strategic Management Journal, 31, pp. 547–561