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RESEARCH ARTICLE

The Role of Collaborations in Successful R&D Projects

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Abstract

R&D and innovation studies often involve complex and highly uncertain tasks, which require experts to work together. This paper aims to investigate how collaboration affects the probability of success for an R&D (Research and Development) project while controlling some other factors or groups. Retrospective data of the projects managed in an R&D Centre of the Scientific and Technological Research Council of Turkey (TUBITAK) are used in the study. A generalized linear model, logit, and mixed-effect logistic regression in order to examine random effects, are implemented for the empirical analyses. In our findings, exceeding the project deadline appeared as a predictor of success in the R&D project, and collaborations' effects on R&D project success are dependent on the type of these projects. It is useful to decide on the number of collaborating institutions, depending on the project type, type of funding, and the aim of the R&D projects. Product development projects aiming at digital government or homeland security will increase their probability of success via collaboration. R&D projects with limited funds, probably have concerns about the extra costs, but as odds ratios increase against expectations, we can conclude that these projects may also benefit from collaboration.

Keywords

R&D Projects, Collaboration, Success Factors, Automated Model Selection

Introduction

R&D and innovation studies usually involve complex and highly uncertain tasks and require different expertise to work together. Sometimes, the results that can be achieved much more efficiently by a simple cooperation are obtained with much more difficultly by trying to create repetitive infrastructure and competences. Of course, it is not expected that cooperation will yield positive results in all circumstances, but it will be beneficial to investigate the effects of collaboration on project success. The main motivation of our study is to examine these collaboration dynamics among the R&D projects, having different aims or types.

Collaboration is an issue for successful innovation. Despite the complexity it brings to the projects, collaboration plays an important role in R&D and innovation. Therefore, most

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governmental R&D policies prioritize collaboration in order to maximize the benefits (e.g., "Triple Helix Model" in Etzkowitz & Leydesdorff, 1995).

It has been pointed out in various studies that benefits can be increased through collaborations, especially among complementary actors (Carayannis & Alexander, 1999; Fernandes, Araújo, Andrade, Pinto, Tereso, & Machado, 2020; Lee & Bozeman, 2005). Complex and highly uncertain tasks of R&D mostly depend on the development and integration of new knowledge and require different experts to work together on new knowledge, which are often not owned by any actor alone. This fact puts the locus of innovation in a network of inter-organizational relationships. But managing these relationships is a difficult task. There are of course benefits through accessing complementary knowledge sources, but there is also a risk of opportunistic behaviour from external partners and costs arising from the communication issues (Cassiman, Di Guardo & Valentini, 2009).

The main motivations for firms to collaborate in R&D are: expecting benefits such as sharing risks and costs of technological development (Baaken, Kesting & Gerstlberger, 2017; Bayona, García-Marco & Huerta., 2001; Carayannis & Alexander, 2004; Das & Teng, 2000; Kang & Kang, 2010), reducing the project term (Pisano, 1990), monitoring technological advances and access to new technology (Hamel, 1991), pooling resources and technological competencies (Carayannis & Alexander, 2004; Das & Teng, 2000), taking advantages of scale and overcoming entry barriers (Hagedoorn, 1993), and forming networks (Diir & Capelli 2018). The main challenges of collaboration are external (natural, political, economic, social risks), internal (strikes, production, or infrastructure problems) and network-related (interaction problems such as management, knowledge management, business processes, and collaboration issues) (Diir & Capelli, 2018).

Contributions to the literature on R&D collaboration concentrate on both theoretical explanations and empirical studies on different forms of R&D cooperation (Kleinknecht & Reijnen, 1991). Theoretical contributions are mainly from game theory (Baniak & Dubina, 2012; Binenbaum, 2008; Gong & Zhang, 2014; Katz, 1986), transaction cost economy, institutional theory, and corporate strategy (Gulati, 1995). Researchers from different theoretical perspectives applied efforts to understand when and why firms enter alliances, or the composition of an alliance (Gulati, 1995). Empirical studies usually investigate the effects of R&D collaboration on R&D success or failure, whether it is defined by product innovation (Kang & Kang, 2010), benefits (Binenbaum, 2008), partnering performance (Mishra, Chandrasekaran & Maccormack, 2015), delays or failures (Lhuillery & Pfister, 2009) or on organizational innovation (Simao & Franco, 2015).

There are conflicting results on the effects of R&D collaboration on innovation. Some research suggests a positive relationship (Aschoff & Schmidt, 2008; Belderbos, Carree & Lokshin, 2004) while others claim the opposite (Okamuro, 2007; Teng, 2006). These results indicate that the factors which determine the effect of R&D collaboration on innovation, are complex. In some studies, the type of partners, also identified as a major factor in this relation (Belderbos et al., 2004; Fritsch & Lukas, 2001; Lhuillery & Pfister, 2009; Tether, 2002). Different partner types own different capabilities and resources, and behave in different manners in an R&D collaboration relationship. These differences affect the efficiency and the profitability of R&D collaboration.

Another focus of the previous research is on the relationship between R&D cooperation and corporate performance. Studies often conclude that R&D cooperation has positive impacts on a firm's innovation performance (Lhuillery & Pfister, 2009).

This paper aims to investigate how collaboration affects the probability of success for an R&D project while controlling some other factors. The paper is organized as follows: After a literature review on collaboration and success in R&D projects; hypotheses are developed. A generalised linear model is used for our empirical analysis. Success is measured via expert judgment, and then the model in logit form is analysed to select important variables with an automated variable selection procedure. Akaike weights and the relative importance of the variables in these sets are examined. Then, the hypotheses were tested with multi-level analyses and the resulting mixed-effect logistic regression model is bootstrapped for asymptotic assumptions' check. Finally, the potential implications are specified in the conclusion, after the discussion of the findings and the lessons learned from the study.

Collaboration and Project Success

R&D project success can be defined by a combination of subjective and objective measures, it depends on the type of innovation and is contextual (Balachandra & Friar, 1997). This lack of clarity leads to different subjective interpretations for practitioners and academics on defining project success (Smith-Doerr, Manev & Rizova, 2004).

Most commonly, a project can be considered as successful if project outputs are delivered with the expected quality on time, outcomes are realized, executed within the budget and the requirements of the stakeholders are met. As Pinto and Slevin (1987) mentioned, it is usually not explicit how to measure the project success, because of the potentially conflicting interests of stakeholders. Project success is dependent on both its success criteria and stakeholders' perception of success (Bond-Barnard, Fletcher & Steyn, 2018).

Some common success factors for R&D projects in the literature are " high-level management support", "high probability of technical success", "market existence", "availability of raw materials and technical skills", "development cost", "commitment and experience of project staff", "communication", "clearly defined project mission and objectives", "well-defined project plan", "monitoring and feedback", "congruent technology with business strategy", "potential financial returns", "customer satisfaction", "interdisciplinary work", "supplier satisfaction" and "staying within budget constraints" (Balachandra & Friar, 1997; Belassi & Tükel 1996; Cooper & Kleinschmidt, 1995; Dwyer & Mellor, 1991; Gaynor, 1996; Griffin & Page, 1993; Maidique & Zirger, 1985; Pinto & Slevin, 1987; Smith-Doerr et al., 2004; Souder & Jenssen, 1999).

In our study, success is measured via the subjective assessment of stakeholders, which implicitly involves innovation issues.

Li, Eden, Hitt, Ireland & Garrett (2012) studied the governance decisions in R&D alliances, analysing a variance between bilateral and multilateral alliances. Their research suggested that collaborating with more partners increases the complexity of managing R&D alliances, and they found that multilateral R&D alliances are more likely to have equity-based governance structures, which are costlier. Knowledge sharing increases when the number of partners increases, but so do the concerns for knowledge leakage.

To sum up, according to the results in different studies, the effects of collaboration on project success (or innovation) may vary depending on the type of R&D, type of collaborating parties, project type, and scale of collaboration. Therefore, it is important to have a contingency approach to collaboration issues, especially for regulating bodies when promoting the collaboration of many actors in an ecosystem.

In many studies, the most common idea concerning the success of R&D projects is that it depends on numerous multi-dimensional factors (Balachandra & Friar, 1997; Cooper & Kleinschmidt, 1995; Griffin & Page, 1993; Hauser, 1998; Kerssens-van Drongelen & Bilderbeek, 1999). To overcome this, Baker, Murphy & Fisher (1983) used "perceived performance", instead of time-cost-performance measures.

Hypothesis Development

Retrospective data of the projects managed in an R&D Centre of the Scientific and Technological Research Council of Turkey (TUBITAK) are used in the study. TUBITAK is a governmental structure with no similar bodies in a developing country like Turkey. This R&D centre especially excels at multidisciplinary and novel research in several areas like informatics, e-government, defence and information security. Therefore, it can be said that choosing this institution to examine the relationship between R&D success and collaborations is the right choice in terms of representation.

The control variables and the dependent variable in this study are introduced in detail in Table 2 to investigate the potential factors which may affect the probability of success for an R&D project. For example, InFin stands for a dummy variable for the use of internal resources, Budget stands for the amount of money which the project is allowed to spend, Expenses stands for the realized spending, BudgetUr stands for the use rate of the budget, Clscore stands for a score calculated via a checklist for project management, FBack stands for a dummy variable if the project is monitored in detail by top management, ProjSize stands for the size in terms of money.

The relation between the common success factors quoted above and the control variables in *Table 2*, and the expected direction of the correlation are shown in *Table* 1:

Table 1
Control Variables and Common Success Factors

Common success factor	Related control variable (s)	Expected direction of correlation
High-Level Management support	InFin and Budget	positive
Development cost	Expenses	negative
Staying within budget constraints	BudgetUr	positive
A well-defined project plan	Clscore	positive
Monitoring and feedback	Fback	positive

In addition to the control variables introduced above, we also included some other controls that may also affect the probability of success into the automated variable selection. These are, project type and five dummy variables (PT) representing these types, RelExp (ratio of expenses to size), four dummy variables for the aim of the project, ExTime (Extra time given to the project), SecLevel (a categorical variable for the security level of the projects), six dummy variables for the type of the funding (FT) and CollCount, which represents the number of different institutions collaborating in the project.

Like findings, which are pointing to the different effects among sectors or types, we expect a difference in the effects of collaboration, according to the type and aim of the projects.

> **H1:** *Collaboration has different effects on the success probability of R&D projects with different project types.*
>
> **H1a:** *If an R&D project is of type technology development, product development, or consultancy and service, these projects are likely to be more successful with the increasing number of collaborating institutions.*
>
> **H1b:** *If an R&D project is of type feasibility or research infrastructure development, projects are likely to be more successful with the decreasing number of collaborating institutions.*
>
> **H2:** *Collaboration has different effects on the success probability of R&D projects of different financial types.*
>
> **H2a:** *If an R&D project is funded internationally or by a collaborative funding prog-*

ram (TARAL[1]), projects are likely to be more successful with the increasing number of collaborating institutions.

H2b: *If an R&D project is funded internally or by limited government funds, projects are likely to be more successful with the decreasing number of collaborating institutions.*

H2c: *If an R&D project is funded by a customer under a contract, the effects of collaboration cannot be predicted.*

H3: *Collaboration has different effects on the success probability of R&D projects with different aims.*

H3a: *If an R&D project is aiming to improve homeland security or social prosperity/ environment or digitalization of governmental activities, projects are likely to be more successful with the increasing number of collaborating institutions.*

H3b: *If an R&D project aiming at economic benefits, projects are likely to be more successful with decreasing number of collaborating institutions.*

Materials and Methods

Data

In this research, 170 completed R&D projects in a public R&D institution, located in Kocaeli (Turkey), were studied using their retrospective data retrieved from the institution's ERP (Enterprise Resources Planning) system, and cleansed, and then analysed as per the criteria regarding the measures of success and the characteristics of successful projects determined in the literature review. In 2015, a new ERP system was established in this institution and those 170 R&D projects were completed after 2015, and therefore, has information inside this new system. The data, which are still considered to be incomplete, were excluded from the analyses (e.g., customer satisfaction, delay, technical performance of the product, resulting technology and/or product in numbers).

While it is already difficult to define project success in general, it is more difficult in R&D projects. Therefore, the dependent variable "success" is measured by expert judgment. These judgments gathered via face-to-face and on-the-phone interviews with a 3-point-scale. Most of these experts were managers, but the main criteria to choose an expert for the interview was "remembering the subjected project well", rather than his/her position in the hierarchy. Judg-

1 TARAL is an acronym for "Türkiye Araştırma Alanı" and most commonly used to indicate a special collaborative research funding programme of The Scientific and Technological Research Council of Turkey.

ments gathered by a three-point scale had a rather unbalanced distribution. So, the dependent variable 'ExpOpin', was re-coded as binary, by converting "Moderate" into "Unsuccessful" and resulted in a better distribution in observations (123 successful vs 47 unsuccessful with a ratio of 2.62). A generalized linear model can be used for binary variables. Since probit and logit models yield similar inferences, we chose the logit model for our empirical analysis. We model a binary outcome variable and, by definition, our data are grouped in terms of project types, aims and financial types, thus explanatory variables have random and fixed effects (Agresti, 2013). The variables and their descriptive statistics are given in Table 2.

Table 2
Variable Definitions and Descriptive Statistics

Variable	Description	Mean	Sd	Med	Min	Max	Type
ExpOpin	(Dependent variable) Subjective expert opinion about the project (0: unsuccessful, 1: successful)	2.65	0.62	3.00	1.00	3.00	Nom
ProjType	PT: R&D, Research infrastructure, Product development, Feasibility, Consulting or Service (1:5)	1.50	0.96	1.00	1.00	5.00	Nom
ClScore	A checklist score for project management: Every 1 point if there is a technical PM assistant, managerial PM assistant, Project plan.	1.13	0.93	1.00	0.00	3.00	Int
InFin	1 if the institutions' own internal financial resources are used, 0 otw	0.38	0.49	0.00	0.00	1.00	Dum
FBack	1 if another detailed tracking system is used in project management, 0 otw	0.64	0.48	1.00	0.00	1.00	Dum
RelExp	Project spending in TL divided by project size in TL	0.83	1.03	0.74	0.00	12.61	Rat
BudgetUr	Use rate for the budget, measured by (budget-spending)/budget	0.16	0.55	0.16	-3.76	1.00	Rat
AimHS	Aim; 1 if the project is for homeland security, 0 otw	0.48	0.50	0.00	0.00	1.00	Dum
AimSE	Aim; 1 if the project is for social or environmental issues, 0 otw	0.16	0.37	0.00	0.00	1.00	Dum
AimDG	Aim; 1 if the project is for digital government, 0 otw	0.21	0.41	0.00	0.00	1.00	Dum
AimEW	Aim; 1 if the project is for economic welfare, 0 otw	0.14	0.35	0.00	0.00	1.00	Dum
ProjTime	Project time in months	35.85	32.78	27.00	0.00	244.00	Int
ExTime	Extra time given for the project in months	7.05	12.08	0.00	0.00	54.00	Int
ProjSize	Financial size of the project given in TL ($x10^9$)	5033.8	10028.1	1355.0	11.0	72808.6	Int
Budget	Financials allowed to spend in the project, given in TL (000)	4373.7	8891.3	1115.5	11.0	61983.2	Int
Expenses	The amount of money spent on the project, in TL (000)	3473.6	6668.6	984.1	0.00	45634.3	Int

Variable	Description	Mean	Sd	Med	Min	Max	Type
SecLevel	The security level of the project: 3 Secret, 2: Restricted, 1: Unclassified, 0: Specific	1.65	0.74	2.00	0.00	3.00	Num
FContr	FT; 1 if the project is financed according to a contract with a customer, 0 otw	0.59	0.49	1.00	0.00	1.00	Dum
FTTaral	FT;1 if the project is financed by a public research fund, 0 otw	0.08	0.28	0.00	0.00	1.00	Dum
FTInt	FT;1 if the project is financed by international funds, 0 otw	0.04	0.20	0.00	0.00	1.00	Dum
FTPub	FT; 1 if the project is financed by a public infrastructure fund, 0 otw	0.07	0.26	0.00	0.00	1.00	Dum
FTIn	FT; 1 if the project is financed by internal funds, 0 otw	0.21	0.41	0.00	0.00	1.00	Dum
FTStSales	FT; 1 if the project has a standard product with a standard price, 0 otw	0.01	0.08	0.00	0.00	1.00	Dum
PTNPD	PT;1 if it is a product development project, 0 otw	0.61	0.49	1.00	0.00	1.00	Dum
PTTechD	PT;1 if it is a technological development project, 0 otw	0.06	0.24	0.00	0.00	1.00	Dum
PTResInf	PT;1 if it is a research infrastructure project, 0 otw	0.04	0.20	0.00	0.00	1.00	Dum
PTCons	PT; 1 if it is a consultancy or service project, 0 otw	0.26	0.44	0.00	0.00	1.00	Dum
PTFeas	PT; 1 if it is a feasibility project, 0 otw	0.03	0.17	0.00	0.00	1.00	Dum
CollCount	The number of different institutions collaborating in the project. 0: no collaboration... 3: 3 different institution (0:3)	1.51	0.81	1.00	1.00	4.00	Int

Note: $n = 170$*. Aim: The aim of the Project. FT: Financial type of the Project. PT: Type of the Project. Dum: Dummy, Rat: Ratio, Int: Integer, Nom: Nominal. Sd: Standard deviation, Med: Median. otw: otherwise.*

Model Selection Procedure

The model is constructed as follows, and analysed to select important variables (Correlated variables are not included in the same set):

$$log\left[\frac{P(Y=1)}{1-P(Y=1)}\right] = logit\ (\pi) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

where, Y_j : 'ExpOpin' for project j (1 for successful, 0 for moderate and unsuccessful), $\pi = P(Y = 1)$,α: intercept,x_i: i^{th} variable, β_i: coefficient for the effect of x_i on the probability of success ($i = 1, \dots, n$).

To avoid subjectivity, an automated variable selection procedure is preferred to decide on the model. This procedure finds the n best models among all possible models for the candidate set. Models are fitted with a generalized linear model (logit in our case) and are ranked with some information criterion (mainly Akaike Criterion (AIC) in our case). The best models are found through exhaustive screening of the candidates. Ten different candidate sets were analysed one by one via this procedure for nearly a month. The size of the candidate sets was between 33.554.432 and 1.048.576.

Variables 'ProjSize', 'RelExp' and 'BudgetUr' were highly correlated with variables 'Budget' and 'Expenses', therefore they are not included in the same trial set. Since 'ProjSize', 'Budget', and 'Expenses' have relatively large values, we used these variables on a logarithmic scale. A summary of the results can be found in Appendix A.

When we examine the models in detail (if we look at the top 10 models for any arbitrary set), the model weight (Akaike weights) for the best model is not substantially smaller than that of the second model. So, it is better to be doubtful about the best model in the set. To consider the variables' contributions, we plot the relative importance of the various model terms in these sets (see Figure 1) (see Appendix B for multi-model inference results -only variables with importance larger than 0.8 included):

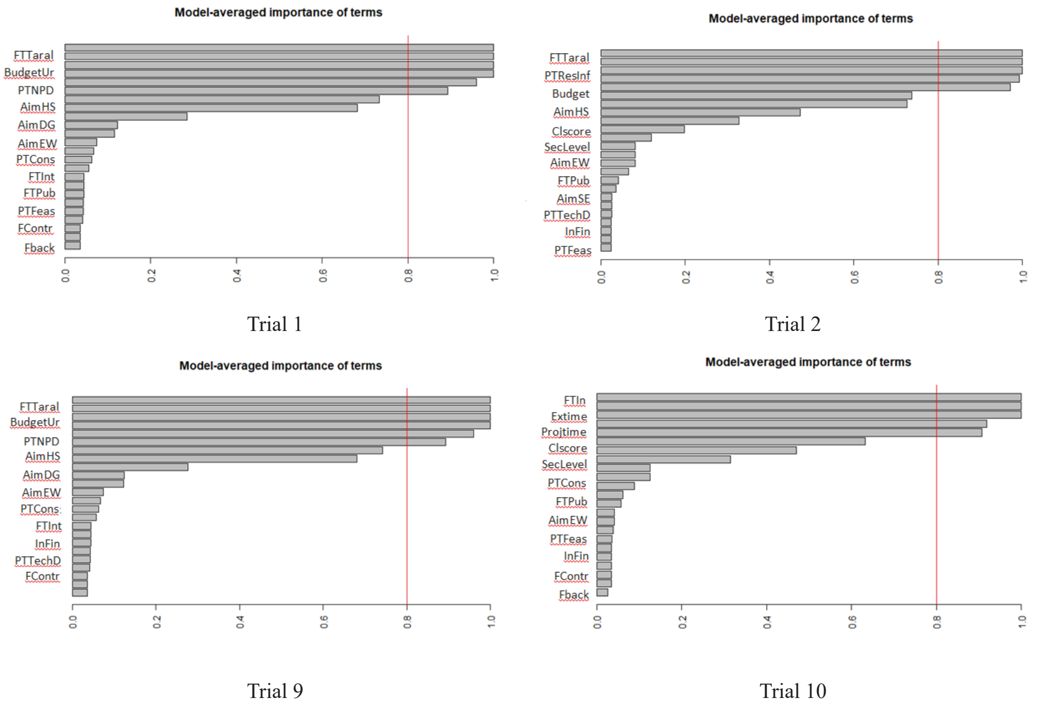

Figure 1. Importance of the variables in the selected models

A particular predictor's importance value is calculated by the sum of the weights (probabilities) for the models that contain the variable. The importance value of a variable is high if it shows up in many models with large weights. Importance values provide overall support for the variable among all candidate models (Burnham & Anderson, 2004; Anderson, 2008).

We see that most of the important variables are also in the best models, but there are differences between them. Some best models include less important variables (like ClScore or Budget). Some dummy variables, especially the ones about project types (financial type and R&D type) are included both in the best models and top variable importance lists, which showed the presence of an effect, related to the type of the project. This pointed out a random-effects model, but it is problematic to look for random effects in an automated model selection procedure. Considering the issue, we decided to select the variables that have high importance values, other than the ones related to the project type. Thus, we implemented several multi-level analyses with those project types and fitted a mixed-effect logistic regression model instead. We investigated the null model and the 7 logistic models (those include the variables “ExTime”, “BudgetUr”, “ProjTime” in different combinations) and chose the model, which has the least AIC value (see Table 3).

Table 3

Multiple Logistic Regression Results for Selected Variables

Variables		**Null Model**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
ExTime	Est.		0.0567				0.0651	0.0600	0.0622
	p-val		*0.014078 **				*0.00825 ***	*0.01103 **	*0.00960 ***
BudgetUr	Est.			0.091		0.0684	0.3229		0.3610
	p-val			*0.763*		*0.825656*	*0.3332*		*0.2790*
ProjTime	Est.				-0.0018	-0.0015	-0.0040	-0.0047	
	p-val				*0.726*	*0.7769*	*0.43624*	*0.36201*	
Intercept	Est.	0.9620	0.6648	0.9481	1.0268	1.0058	0.7178	0.8168	0.5796
	p-val	*<0.001 ****	*0.0007 ****	*<0.001 ****	*<0.001 ****	*0.00021 ****	*0.0097 ***	*0.0016 ***	*0.0060 ***
Ndev-Resdev		0	8.82	0.09	0.12	0.17	10.54	9.64	9.95
df			1	1	1	2	3	2	2
AIC		202.46	**195.64**	204.37	204.34	206.29	197.92	196.82	196.51
Correctly Predicted (Ratio)			0.7235	0.7235	0.7235	0.7235	0.7235	0.7176	0.7294
ANOVA (Type II Wald)									
ExTime	$\chi^2(1)$		6.0284				6.9780	6.4599	6.7081
	p-val		*0.0141 **				*0.0083***	*0.0110 **	*0.0096 ***
BudgetUr	$\chi^2(1)$			0.0913		0.0485	0.9363		1.1718
	p-val			*0.7625*		*0.8257*	*0.3332*		*0.2790*
ProjTime	$\chi^2(1)$				0.1228	0.0803	0.6062	0.8309	
	p-val				*0.7260*	*0.7769*	*0.4362*	*0.3620*	
Hosmer and Lemeshow goodness of fit (GOF) test									
	$\chi^2(8)$		2.6897	7.8994	7.6645	13.352	7.6611	7.0825	11.713
	p-val		*0.9523*	*0.4434*	*0.4669*	*0.1003*	*0.4673*	*0.5278*	0.1645

Variables	Null Model	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Pseudo R2 (vs Model null)								
McFadden		0.0440	0.0004	0.0006	0.0008	0.0526	0.0481	0.0496
Cox & Snell (ML)		0.0506	0.0005	0.0007	0.001	0.0601	0.0551	0.0568
Nagelkerke (Cragg&Uhler)		0.0730	0.0007	0.0010	0.0014	0.0868	0.0796	0.0821
Likelihood Ratio Test								
χ^2		8.8213	0.0894	0.1207	0.1685	10.545	9.6434	9.9461
p-val		*0.0030***	*0.7649*	*0.7283*	*0.9191*	*0.0145**	*0.0081***	*0.0069***
df diff		-1	-1	-1	-2	-3	-2	-2

(.) p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Findings from Selected Models

Model 1 ($logit\ (\pi) = 0.665 + 0.0567x_{ExTime}$) has the least AIC and the largest p-value for Hosmer (0.9523>0.05). We see that 'ExTime' has a positive effect on perceived project success ('ExpOpin') in all the models and it is the only variable that has p-values<0.05. Extra time may be a signal for great expectations for a project, so it may lead to a positive perception of success. Although there are satisfactory results for some goodness of fit tests like ANOVA (Analysis of Variance) and Hosmer, pseudo R^2 values are rather small. Therefore, we investigated random effects among different project typologies. 'Type of the project'(PT_f), is the dummy code of the variables PTNPD, PTTechD, PTResInf, PTCons, PTFeas, 'Financial type of the project'(FT_f), is the dummy code of the variables FContr, FTTaral, FTInt, FTPub, FTIn, FTS, and 'Aim of the project'(Aim_f), is the dummy code of the variables AimHS, AimSE, AimDG, Aim EW. We fit a mixed-effect logistic regression to see the possible random effects of these factors, in model 8.

We then fit mixed-effect logistic regression to check our hypotheses 1, 2, and 3 for the effects of collaborations (CollCount) on project success, and the potential variability of these effects among the project types; in models 9, 10, and 11 (see Table 4). The mixed-effect models are represented as follows:

Model 8: $g(\mu_{ij}) = \alpha + \beta x_{jExTime} + u_{PT\_f} Z_{iPT\_f} + u_{FT\_f} Z_{iFT\_f} + u_{Aim\_fc} Z_{iAim\_f} + \varepsilon_{ij}$

Model 9: $g(\mu_{ij}) = \alpha + \beta x_{jExTime} + u_{0PT\_f} + u_i Z_{iCollCount} | Z_{iPT\_f} + \varepsilon_{ij}$

Model 10: $g(\mu_{ij}) = \alpha + \beta x_{jExTime} + u_{0FT\_f} + u_i Z_{iCollCount} | Z_{iFT\_f} + \varepsilon_{ij}$

Model 11: $g(\mu_{ij}) = \alpha + \beta x_{jExTime} + u_{0Aim\_f} + u_i Z_{iCollCount} | Z_{iAim\_f} + \varepsilon_{ij}$

where y_{ij} is 'ExpOpin' for the project j in category i, Z_i denotes the relevant (explanatory) random variables with random effects of u, α is for the intercept, $x_{jExTime}$ is the explanatory variable (ExTime) for project j with fixed effect β and $\mu_{ij} = E(Y_{ij} | u_i)$, whereas ε_{ij} is representing the residuals.

Table 4
Mixed Effect Logistic Regression Results

Fixed Effects		Model 8	Model 9	Model 10	Model 11
ExTime	Est.	0.0645	0.05837	0.06674	0.06346
	p-val	*0.0135 **	*0.01407 **	*0.00873 ***	*0.00956 ***
Intercept	Est.	0.3555	0.60956	0.42328	0.75652
	p-val	*0.4699*	*0.00809 ***	*0.31472*	*0.00190 ***
Random Effects					
PT (intercept)	S.D.	0.0000	0.3913		
Aim (intercept)	S.D.	0.0996			0.2178
FT (intercept)	S.D.	0.8788		1.1983	
CollCount1	S.D.		0.6400	0.5761	0.5036
CollCount2	S.D.		0.7630	0.1458	1.4227
CollCount3	S.D.		0.6497	1.4615	27.8455
AIC		183.1	215.2	195.0	207.0
Correctly Predicted (Ratio)		0.8	0.7294	0.8235	0.7529
ANOVA (Type II Wald)					
	ExTime	6.1058	6.0287	6.8771	6.7149
	p-val	*0.01347 **	*0.01407 **	*0.00873 ***	*0.00956 ***
Hosmer and Lemeshow test					
	$\chi^2(8)$	10.219	6.4515	6.1124	
	p-val	*0.25*	*0.5968*	*0.6346*	
Pseudo R^2 (vs Model null)					
McFadden		0.1365	0.04628	0.1468	0.0869
Cox & Snell (ML)		0.1486	0.05311	0.1589	0.0974
Nagelkerke (Cragg &Uhler)		0.2147	0.07669	0.2296	0.1406
Likelihood Ratio Test		**Model 8**	**Model 9**	**Model 10**	**Model 11**
	χ^2	27.3580	9.2773	29.4370	17.4190
	p-val	*<0.001****	*0.5963*	*0.00194***	*0.0961(.)*
	df diff	-4	-11	-11	-11

Note: S.D. is for standard deviation, S.E. is for standard error

According to ANOVA, all models indicate a significant effect for ExTime with all p-values being less than 0.05. Similarly, Hosmer and Lemeshow's tests show no evidence of not-fit for all the models, which have p-values bigger than 0.05.[2] Model 8 and Model 10 both have higher Pseudo R^2 values, lower AIC values, and both models also predict success correctly, more than 80 percent.

Standard errors for random effects imply the variability in the intercept, according to the category (bigger the deviation, bigger the need for control). As expected, this is large (0.8788) for the category 'financial type of the project'.

2 Also, larger McFadden's pseudo R^2 values indicate a better fit than smaller ones (A model with McFadden pseudo R^2 less than 0.2 is likely not slightly bad but by this metric, it isn't strong either). Nagelkerke and Cox&Snell measures give similar results, the latter being more conservative with smaller values. A Cox&Snell pseudo R^2 statistic of 0.1589 (Model10) is generally interpreted to mean, the ExTime independent variable in the model account for 15.89 percent of the explanation for a project's success according to expert opinion.

In models 9, 10, and 11; the big standard errors of random effects for collaborations point to the variability of these effects on project success, according to the categories 'Type of the project', 'Financial type of the project' and 'Aim of the project' respectively. Model 10 fits slightly better, according to the goodness of fit tests among these three models.

Intercept in model 9 will vary according to the project type (PT) approximately 16% (0.64/4)[3] in the case of collaboration with one entity, app. 19% (0.7630/4) in the case of collaboration with two entities, app. 16% (0.6497/4) in the case of collaboration with three entities. In product development and technology development projects, it is preferred to collaborate more, to combine competencies in a pool to increase capabilities. Therefore, it is expected that project success probability will increase with collaboration for the types 2 (consultancy and service), 4 (technology development), and 5 (product development); whereas types 1 (feasibility) and 3 (research infrastructure) would demand fewer parties in the project. In mixed-effect logistic models, odds ratios stand for the non-standardized effect size, therefore we checked these ratios (see Appendix C). When we examine the odds ratios, effect sizes decrease for types 1 and 3 and increase for 2 and 5 as expected, but decrease for type 4, against expectations. Therefore, our H1b of "If an R&D project is of type feasibility or research infrastructure development, projects are likely to be more successful with the decreasing number of collaborating institutions" is supported and H1a of "If an R&D project is of type technology development, product development, or consultancy and service, these projects are likely to be more successful with the increasing number of collaborating institutions" is not supported only for technology development projects and supported for others.

Intercept in model 10 will vary according to the project financial type (FT) approximately 14% (0.5761/4) in the case of collaboration with one entity, app. 3% (0.1458/4) in the case of collaboration with two entities, app. 37% (1.4615/4) in the case of collaboration with three entities. Collaboration is expected to be a necessity for international (type 3) and TARAL projects (type 4) and the opposite for self-financed (type 1) and government-financed (type 2) projects because of the collaboration costs. It is expected for the odds ratios to increase with collaboration for types 3 and 4, decrease for types 1 and 2, both possible for type 5 (contractual). When we examine the odds, 3 and 4 increase as expected, but the others also increased with collaboration against expectations. For contractual projects, collaboration with two different entities has more effect size. Therefore, our H2b of "If an R&D project is funded internally or by limited government funds, projects are likely to be more successful with the decreasing number of collaborating institutions." is not supported, while H2a "If an R&D project is funded internationally or by a collaborative funding program (TARAL), projects are likely to be more successful with the increasing number of collaborating institutions" and H2c "If an R&D project is funded by a customer under a contract, it is hard to predict the effects of collaboration" supported.

Intercept in model 11 will vary according to the aim of the project (Aim) approximately 13% (0.5036/4) in the case of collaboration with one entity, app. 36% (1.4227/4) in the case of collaboration with two entities, app. 696% (27.8455/4) in the case of collaboration with three entities. It is expected that collaboration will increase the probability of success for the projects aiming to improve homeland security (type 4) or social prosperity/environment (type 3) or digital government (type 2), whereas decrease for the projects with economic goals (type 1). When we check the odds ratios, effect sizes increase for digital government and security projects as expected; but collaboration of more than two entities in economic and social prosperity/environment projects tend to decrease the probability of success. The huge effect size for security projects shows the importance of broad participation of potential stakeholders for this type. Our H3a of "If an R&D project is aiming to improve homeland security or social prosperity/environment or digitalization of governmental activities, projects are likely to be more successful with the increasing number of collaborating institutions" is not supported for social prosperity/environment projects and supported for others. H3b of "If an R&D project aiming at economic gains, projects are likely to be more successful with decreasing number of collaborating institutions" is supported.

The goodness of fit tests points to the mixed effect logistic regression "model 10" for a better fit. Due to the limited sample size, refitting the model and estimating the bootstrap parameters demonstrate how robust the results are. Therefore, this model is used to check the asymptotic assumptions via bootstrap estimations with 1000 replications. Bootstrap medians, standard errors, biases, and confidence intervals are given in Table 5.

Table 5
Bootstrap Results

	Orig.	Boot Biases	Boot SE	Boot Med.	CI Normal 95%	CI Basic 95%	CI Perc. 95%
Intercept	0.894	0.110	0.604	0.984	(-0.34, 1.97)	(-0.62, 1.87)	(-0.10, 2.40)
ExTime	0.806	0.097	0.390	0.858	(-0.06, 1.47)	(-0.25, 1.33)	(0.28, 1.86)
Intercept SD	1.198	-0.125	0.795	0.952	(-0.23, 2.88)	(-0.53, 2.40)	(0.00, 2.93)
CollCount1 SD	0.576	0.380	0.890	0.792	(-1.55, 1.94)	(-1.95, 1.12)	(0.03, 3.10)
CollCount2 SD	0.146	1.623	5.548	0.800	(-12.35, 9.40)	(-6.29, 0.26)	(0.03, 6.58)
CollCount3 SD	1.461	4.935	14.405	1.928	(-31.71, 24.76)	(-52.26, 2.85)	(0.07, 55.18)

Note: S.D. is for standard deviation

Bootstrap biases and standard deviations are sufficiently small for 'intercept', 'ExTime', 'sigma for FT intercept', and 'sigma for CollCount 1'. When we examine the histograms of the bootstrap estimations for observations resampling in Appendix D, distributions for random effects are skewed to the left as expected, and close to normal for the fixed effects.

Results and Discussion

In the examined models with lower AICs, the "ExTime" variable appears to have a positive effect on perceived success ("ExpOpin") of R&D projects. This indicates the extraordinary nature of R&D projects. If stakeholders accept to give extra time to the project, most probably the R&D project shows promising results and proceeding in the new direction becomes a crucial issue for success, more than the planned due dates or project management performance do. In the early stages of research, it is more likely to deviate from planned duration, regarding the high uncertainty in it. As Hauser (1998) stated that criteria choices should differ according to the type of R&D (basic research, core technological development or applied research), perception of success is expected to differ among these groups. However, we could not find any random effects specific to the project type regarding the extra time in our data.

In addition to ExTime, ProjTime has high importance in trial 10, which is following Bizan's (2003) finding of the coherent increase in project duration and technical success.

In our models based on different features of the projects; "type", "financial type" and "aim"; encountering large standard errors in measuring the random effects of collaborations shows the large variability of these effects on project success. Cooper & Kleinschmidt (1995), Dwyer & Mellor (1991), Gaynor (1996), Maidique & Zirger (1985), and Souder & Jenssen (1999) show interdisciplinary work as a success factor for R&D projects. Collaboration often makes this interdisciplinary work less costly, and product development projects benefit from it.

Considering feasibility projects, which are usually small budgeted basic research projects, or research infrastructure projects, which are funded by the limited government funds; collaboration is sometimes not preferred due to the cost of collaboration and concerns on intellectual property rights. In our findings, decreasing effect sizes for collaboration in both feasibility and research infrastructure projects support these expectations.

Although the need for interdisciplinary work and resource pool increases the expectation of collaboration for technology development projects, the effect sizes in our findings decrease. The reason for this may be that technology development projects in this Institution are similar to feasibility projects in terms of budget size and complex IPR issues.

Effect sizes increase for projects, aiming at digital government and homeland security, as the collaborating institutions increase. These R&D projects often have so many stakeholders in hand, and success probability naturally increases when more of them collaborate.

Lessons Learned

There are limitations in this study, mainly the subjective nature of the dependent variable. Incomplete data are excluded from the analysis, and therefore, customer satisfaction, which is regarded as one of the main factors and measures for success (Cooper & Kleinschmidt, 1995; Dwyer & Mellor, 1991; Gaynor, 1996; Griffin & Page, 1993; Maidique & Zirger, 1985; Souder & Jenssen, 1999; Pinto & Slevin, 1987), could not be analysed. This is because customer satisfaction is measured by general surveys at this Institute without directly addressing the projects. Other important limitations are the lack of criteria regarding the technical performance of the project outputs and the generalizability of results. These findings may be valid for similar countries by means of culture and/or Global Innovation Index ranks, but higher ranked and/or developed countries may be subject to different dynamics. Further studies that take these problems into account and use larger samples will deepen the results of this study.

Conclusions

This study aims to shed light on the uncertain and complex nature of R&D projects by investigating the possible effects of R&D collaborations. Our findings also contribute to efforts to understand the differences between "projects" and "R&D projects." For example, in the project management literature, exceeding the project deadline is a feature for failed projects, but on the contrary, it may be a predictor of success in the R&D project.

As reviewed in the literature, there are common success factors for R&D projects, but only extra time stood out among these control variables. Therefore, following the literature claiming the complexity of R&D, we can conclude that predicting the probability of success of an R&D project is not an easy task.

Policymakers often encourage any collaboration in R&D, but indeed the impact of multilateral collaborations on R&D project success depends on the type of these projects.

It will be useful to decide on the number of collaborating institutions, depending on the type, funding type, and the aim of the R&D projects. Product development projects, especially targeting digital government applications or homeland security, will increase the probability of success with collaboration. As Li et al. (2012) stated in their work, increasing the number of partners adds extra complexities to alliance management. Therefore, limited budget R&D projects are likely to have concerns about extra costs, but as the odds ratios increase against expectations, we may conclude that these projects can also benefit from collaboration.

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Appendices

A. Brief Summary of Model Selection Results

Trial No.	Variable Set	Selected Best Model's Response Variables	Best AIC	Evid. Weig.	Worst AIC	*	**
1	3-6,7-14,17-29	BudgetUr,AimHS,ProjTime,ExTime,FTTaral,FTIn,PTNPD,PTResInf	162.524	0.031	165.54	24	92
2	3-5,8-13,15-29	Budget,ProjTime,ExTime,FTTaral,FTIn,PTNPD,PTResInf	165.469	0.024	167.80	57	93
3	3-5,8-13,15-29	Budget,ProjTime,ExTime,FTTaral,FTIn,PTNPD,PTResInf	165.469	0.024	167.89	49	93
4	2-5,8-13,15-29	Budget,ProjTime,ExTime,FTTaral,FTPub,FTIn	169.012	0.025	171.52	49	93
5	2-6,7-14,17-23,29	BudgetUr,AimHS,ExTime,FTTaral,FTPub,FTIn	168.081	0.025	170.62	47	93
6	3-5, 8-13,15-29	ProjTime,ExTime,FTTaral,FTIn,PTNPD,PTResInf	166.167	0.025	168.67	42	93
7	2-5, 8-13,15-23,29	ClScore,ProjTime,ExTime,FTTaral,FTPub,FTIn	169.594	0.026	172.21	41	92
8	2-14,17-23,29	BudgetUr,AimHS,ExTime,FTTaral,FTPub,FTIn	168.081	0.025	170.62	47	93
9	3-14,17-29	BudgetUr,AimHS,ProjTime,ExTime,FTTaral,FTIn,PTNPD,PTResInf	162.524	0.031	165.54	24	92
10	3-5,8-13,15-29	BudgetUr,AimHS,ProjTime,ExTime,FTTaral,FTIn,PTNPD,PTResInf	162.524	0.031	165.54	24	92

***Note**: * for Models within 2 IC (information criterion). ** for Models to reach %95 evidence Weight. Variables 14, 15, 16 are used in the log scale.*

B. Inferences from Model Selection Procedure

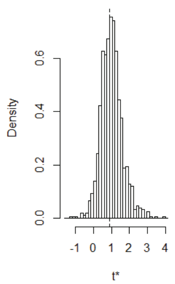
Trial	Variable	Estimate	S.E.	Importance	z value	Pr(>|z|)	CI.lb	CI.ub
1	(Intercept)	1.1903	0.566	1	2.102	0.036	0.080	2.300
	BudgetUr	1.0311	0.449	1	2.297	0.022	0.151	1.911
	ExTime	0.1033	0.035	1	2.966	0.003	0.035	0.172
	FTTaral	-3.1072	0.940	1	-3.305	0.001	-4.950	-1.264
	FTIn	-2.3100	0.561	1	-4.118	0.000	-3.409	-1.211
	PTResInf	-2.0877	1.089	0.96	-1.917	0.055	-4.223	0.047
	PTNPD	0.8871	0.577	0.89	1.539	0.124	-0.243	2.017
2	(Intercept)	1.6679	0.547	1	3.047	0.002	0.595	2.741
	ExTime	0.0847	0.031	1	2.747	0.006	0.024	0.145
	FTTaral	-2.8359	0.881	1	-3.217	0.001	-4.564	-1.108
	FTIn	-2.1876	0.534	1	-4.093	0.000	-3.235	-1.140
	PTResInf	-2.1839	1.069	0.99	-2.043	0.041	-4.279	-0.089
	ProjTime	-0.0174	0.008	0.97	-2.057	0.040	-0.034	-0.001

3	(Intercept)	1.6791	0.539	1	3.117	0.002	0.623	2.735
	ExTime	0.0847	0.031	1	2.757	0.006	0.025	0.145
	FTTaral	-2.8315	0.879	1	-3.221	0.001	-4.554	-1.109
	FTIn	-2.1846	0.535	1	-4.083	0.000	-3.233	-1.136
	PTResInf	-2.1991	1.072	0.98	-2.051	0.040	-4.301	-0.097
	ProjTime	-0.0171	0.008	0.96	-2.007	0.045	-0.034	0.000
4	(Intercept)	1.0854	1.002	1	1.083	0.279	-0.878	3.049
	ExTime	0.0748	0.028	1	2.676	0.008	0.020	0.130
	ProjTime	-0.0132	0.008	0.92	-1.669	0.095	-0.029	0.002
5	(Intercept)	0.9768	0.899	1	1.087	0.277	-0.785	2.738
	ExTime	0.0921	0.031	1	2.939	0.003	0.031	0.154
	BudgetUr	0.7597	0.449	0.93	1.693	0.091	-0.120	1.639
	FTTaral	-2.2417	1.332	0.83	-1.683	0.092	-4.852	0.369
6	(Intercept)	1.4908	0.587	1	2.541	0.011	0.341	2.641
	ExTime	0.0802	0.029	1	2.727	0.006	0.023	0.138
	FTTaral	-2.7958	0.862	1	-3.244	0.001	-4.485	-1.107
	FTIn	-2.1677	0.529	1	-4.099	0.000	-3.204	-1.131
	PTResInf	-1.9277	1.096	0.93	-1.758	0.079	-4.077	0.221
	ProjTime	-0.0107	0.007	0.89	-1.495	0.135	-0.025	0.003
7	(Intercept)	0.9844	0.925	1	1.065	0.287	-0.828	2.797
	ExTime	0.0765	0.028	1	2.710	0.007	0.021	0.132
8	(Intercept)	0.9817	0.925	1	1.062	0.288	-0.831	2.794
	ExTime	0.0922	0.031	1	2.939	0.003	0.031	0.154
	BudgetUr	0.7605	0.449	0.91	1.694	0.090	-0.119	1.640
	FTTaral	-2.2411	1.333	0.83	-1.682	0.093	-4.853	0.371
9	(Intercept)	1.1895	0.609	1	1.952	0.051	-0.005	2.384
	BudgetUr	1.0295	0.448	1	2.296	0.022	0.151	1.908
	ExTime	0.1032	0.035	1	2.963	0.003	0.035	0.172
	FTTaral	-3.1066	0.940	1	-3.303	0.001	-4.950	-1.263
	FTIn	-2.3101	0.561	1	-4.118	0.000	-3.410	-1.211
	PTResInf	-2.0849	1.090	0.96	-1.913	0.056	-4.222	0.052
	PTNPD	0.8886	0.577	0.89	1.539	0.124	-0.243	2.020
10	(Intercept)	1.4552	0.588	1	2.475	0.013	0.303	2.608
	ExTime	0.0799	0.029	1	2.714	0.007	0.022	0.138
	FTTaral	-2.8040	0.862	1	-3.255	0.001	-4.492	-1.116
	FTIn	-2.1738	0.525	1	-4.138	0.000	-3.203	-1.144
	PTResInf	-1.8747	1.108	0.92	-1.692	0.091	-4.046	0.297
	ProjTime	-0.0111	0.007	0.91	-1.559	0.119	-0.025	0.003

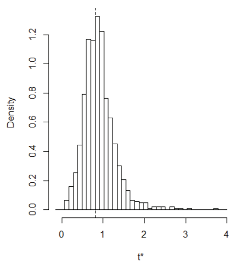
C. Odds Ratios

Odds	**CollCount1**	**CollCount2**	**CollCount3**	**ExTime**	**Intercept**
Model 9					
ProType1	1.2708	0.7515	0.7840	1.060	1.5889
ProType2	0.5907	1.8734	1.7066	1.060	2.5384
ProType3	2.0526	0.4243	0.4819	1.060	1.1851
ProType4	1.2962	0.7340	0.7685	1.060	1.5698
ProType5	0.9092	1.1202	1.1015	1.060	1.9499
Model 10					
FinType1	1.5446	1.1164	3.0131	1.069	0.6181
FinType2	1.2771	1.0639	1.8600	1.069	0.9180
FinType3	1.1542	1.0370	1.4387	1.069	1.1332
FinType4	2.0966	1.2061	6.5412	1.069	0.3274
FinType5	0.5624	0.8644	0.2322	1.069	5.055
Model 11					
Aim1	1.3475	2.3490	9.4051e-05	1.0655	2.4183
Aim2	1.2896	1.9151	60.5746	1.0655	2.2915
Aim3	1.4059	2.6585	2.0803e-05	1.0655	2.4669
Aim4	0.6129	0.2434	12532931	1.0655	1.7223

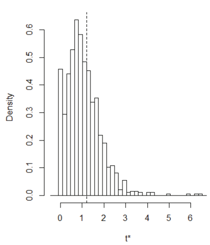
D. Histograms for Bootstrap (with 1000 replicates)



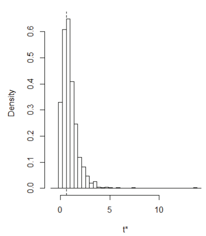
Histogram for Intercept



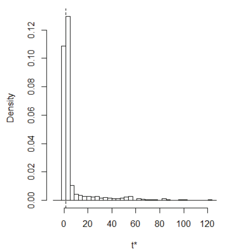
Histogram for ExTime



Histogram for CollCount1



Histogram for CollCount 2



Histogram for CollCount 3