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PLS Path Modeling for causal detection of project management skills: a research field in National Research Council in Italy

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Partial Least Squares Path Modeling is suitably defined and applied in a research field in the largest public research organization in Italy, namely the National Research Council (CNR). In literature studies on Project Management (PM) mostly cover the industry sector rather than the world of science and research. A model with theoretical constructs and latent variables is introduced to analyze the causal detection among different types of variables, including the activation of hard and soft PM skills of Principal Investigators in public organizations. Their activation becomes crucial to improve the management of research projects toward efficiency and effectiveness. Furthermore, high levels of awareness of project goals and tasks to be done influence the activation of PM competencies. Our study particularly highlights how the Leadership capability of a research group manager facilitates positively other soft skills among the Principal Investigators within the science sector.

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1 Introduction

Framework of this paper is the use of Project Management (PM) competencies when dealing with projects developed in the world of science a research. In literature studies on PM of R&D projects mostly cover the industry sector rather than national laboratories and research institutes (Kuchta et al., 2017; vom Brocke and Lippe, 2015; Ernø-Kjølhede et al., 2000). In public research world PM skills are becoming increasingly necessary. The amount of public funds allocated to scientific research has been decreased during the last years so that it is necessary to improve the management of the research projects toward the efficiency. Furthermore, the researchers of public institutions need to be very active continually in fund raising to support their research through national and international cooperation with public as well as private structures. While in the private sector all steps of design, planning and realization of the objectives of a research project in compliance with precise constraints (time, cost, resources, scope, quality) are provided by a Project Manager or supported by Project Management Offices, in the public research institutes researchers are very rarely supported by Project Management Offices and all activities related to project planning and monitoring are done by themselves. Those in charge of research projects must therefore not only have high scientific skills but also have to be able to ensure that the deliverables of the research project are adequate to stakeholder expectations and that are respected the budget and time schedule. Research project managers need to develop PM skills, and this typically requires a radical departure from the skills these scientists initially relied upon for their success (Lounsbury et al., 2012). The transition from carrying out research to managing research projects is difficult because of the specific traits of scientists, their backgrounds, and the fact that little project management training is provided for R&D personnel (Kerzner, 1981). In our view, the need for appropriate PM skills is also motivated by some of the characteristics of the research projects, such as:

- the variation of the scope and the high levels of uncertainty and risk connected to their implementation (Kuchta et al., 2017),
- the high frequence of changes during the life cycle of the project (Blake, 1978),
- the uncertainty of working method and outcome (Turner and Cochrane, 1993). As a consequence, R&D managers have to manage uncertainty through the adoption of appropriate planning and monitoring methods (vom Brocke and Lippe, 2015) and need ability to re-plan or add new tasks to project to respond to uncertainty Lenfle (2008),
- the high number of researchers participating in projects and their heterogeneity. Academic research projects usually refers to cross-disciplinary research that combines researchers from several disciplines and academic institutions working

together with firms and other public bodies and partners that can reside anywhere in the world (vom Brocke and Lippe, 2015; Dewulf et al., 2007; Huutoniemi et al., 2010).

Our paper aims to contribute by filling this lack of information through a field analysis on PM skills of the Principal Investigator of research projects in public research institutions. In our research, starting from the literature background on PM competencies, we selected those skills that are more related to the specific features of the research projects in public research organizations. The list includes both competencies concerning the PM methods (scope, time, cost, risk) and soft skills (leading, research team management, effectiveness, communicating). On the basis of this list we design the questionnaire of our survey carried out on PI of research projects at the Biology, Agriculture and Food Sciences Department (DISBA) of the National Research Council (CNR, Consiglio Nazionale delle Ricerche), i.e., the largest Italian public organization set up to support scientific and technological research supervised by the Ministry of Education, Universities and Research (MIUR).

Our field analysis aims not only to provide an exploratory analysis of the main skills of PM belonging to the PI of research projects but also to verify the validity of three specific hypotheses concerning the activation of PM skills that have not been so far considered in the science and research world:

1. a high degree of awareness of project goals and methods for accomplishing them among Principal Investigators may influence the activation of PM process competencies;
2. a low degree of awareness of project goals and methods for accomplishing them among Principal Investigators may influence the activation of soft skills in PI;
3. the activation of leadership competencies among PIs may influence the activation of other soft skills.

We define a theoretical model to analyze the causal relationships among the different types of variables of interest that fit to the above-mentioned hypotheses. In our theory, the multiple hypotheses involve theoretical constructs (i.e., Awareness, Leadership, etc.) that are represented by latent variables not directly observed but inferred from a statistical model using measurements of observed variables. For that, we established a research field in order to measure a set of measurable variables of interest, some of which describe the mean features of the PI and the research projects that are managed in the public sector, while others are fundamental for inferring the constructs and verifying the significance of our research hypotheses. The most suitable statistical approach for verifying our theoretical model is to use the Structural Equation Modeling (SEM) family, which is widely used in the behavioral sciences (Kaplan, 2008). Specifically, we consider Partial Least Squares Path Modeling (PLS-PM) (Esposito Vinzi et al., 2010; Tenenhaus et al., 2005). SEM has been applied by a growing number of researchers from various disciplines, such as accounting (Lee et al., 2011), strategic management (Hulland, 1999),

management information systems (e.g. Dibbern et al., 2004), e-business (e.g. Pavlou and Chai, 2002), organizational behavior(e.g. Higgins et al., 1992), marketing (e.g. Reinartz et al., 2004), and consumer behavior (e.g. Fornell and Robinson, 1983). This paper provides PLS-PM for causal detection of PM skills in our research field.
The paper is structured as follows. The theoretical background, research hypotheses and the structural model will be discussed in section 2. The research field will be broadly described in section 3. Section 4 contains a discussion of the results of statistical data analysis. Discussion of the results and concluding remarks end the paper (section 5).

2 Literature review, research hypotheses and statistical methodology

2.1 Literature review and research hypotheses

A classification of research projects useful for deciding how the research projects should be managed was proposed by Turner and Cochrane (1993). It is based on the following two parameters: whether the goals are well defined and whether the method for achieving said goals is well defined. According to these parameters, Turner and Cochrane proposed their well known "goal and methods matrix" which identifies four different typologies of projects and makes it possible to select the most appropriate form of PM for each type of project. Crawford and Pollack (2004) consider the degree of classification of goals and methods to be one of the seven classification criteria to adopt to define a "spectrum", distinguishing "hard projects" from "soft projects" and "hard dimensions" from "soft dimensions" in PM. Atkinson et al. (2006) also use the classification drawn up by Crawford and Pollack and refer to projects at the "hard end of the spectrum" and projects at the "soft end of the spectrum." The second case refers to projects with ambiguously defined goals managed by negotiation and discussion. Turner and Payne (1997) state that research projects typically have poorly defined goals and methods. But more recent literature is not in unanimous agreement. In their research, Barnes et al. (2002) highlight that "while the nature of research projects is such that the end results are often difficult to predict, clearly defined objectives (even if they change as the project progresses) provide the basis for a robust and focused research process." According to the PM in R&D White Paper (Energy Facility Contractors Group, 2010), research projects may also belong to the type 2 (well defined goals, poorly defined methods) and type 3 projects (well defined methods, poorly defined goals) identified by Turner and Cochrane (1993), and not only to type 4. More recently, Kuchta et al. (2017) conducted a web survey on a large sample of Polish R&D projects that had won calls for proposals, and they found results contrasting with Turner and Payne. Only 23.19% of projects belonged to the "poorly defined goal/poorly defined methods" category, and 23.91% of projects belonged to the "well defined goal and methods category. This last case regards, for example, research projects co-financed using public funding.
Our assumption is that research projects carried out at public research centers belongs to all four typologies of projects as defined by Turner and Cochrane (1993). As Gustavsson

and Hallin (2014) point out, the dichotomy between the "hard" and "soft" dimensions of projects is also used in literature for PM skills. The authors highlight that "hard skills" are related to the rational and technical side of projects and PM, while "soft skills" are related to the human side of projects and PM. "Hard skills" include planning, scheduling, and controlling as well as monitoring quality and risk analysis. "Soft skills," conversely, are thought to comprise negotiation, change management, and the ability to understand and address the needs of customers, peers, staff and managers. Pollack (2007) highlighted that while project practice based on "hard" projects centers on assessment based on predetermined goals, practice based on the soft paradigm emphasizes learning and participation. According to Kuchta et al. (2017), if the degree of knowledge of goals and methods is not high, as in the case of "soft projects," a traditional PM approach based on detailed initial planning of the projects scope, timeframe, and costs, with subsequent periodical monitoring is not appropriate, and the "Soft approach," based on Agile Project Management, is more suitable. Thus, accomplishing project goals mostly depends on the Project Managers ability to lead by means of communication with others (DuBrin, 2004), his or her ability to influence the project team (Koontz and Weihrich, 1990), better relationships between team members (Nelson and Cooprider, 1996), and the ability to facilitate team cohesiveness (Dionne et al., 2004). Bonner (2010) highlight that managers of agile projects "act as leaders, facilitators and coaches." They "do not look only to a plan consisting of schedule, scope and resource estimates," and "guidance is provided by relying on their ability to influence the team rather than on formal authority." Conboy and Coyle (2010) highlight that the most appropriate management style for Agile projects is one based on leadership and collaboration, while command and control are more appropriate for traditional projects. Takey and de Carvalho (2015) also distinguish between hard and soft Project Management skills. In their view, the competency frameworks for project managers proposed by PM associations and institutes (AIPM, 2008; Association et al., 2006; PMI, 2007) "recommend competency mapping in both hard and soft skills, but focus on hard skills," while in literature "the number of studies with a focus on soft skills is increasing." The authors, on the basis on an in-depth literature analysis, propose a classification of PM that distinguishes between *Project Management Process Competences* and *Personal Competencies*. The former consist of integration management, scope management, time management, costs management, quality management, human resource management, communication management, risk management, contract management, environmental management, and safety and health management. *Personal Competencies* consist of leadership capability, communication, openness, relationships, team building, teamwork, development of others, conflict resolution, holistic view, systemic view, assertiveness, problem-solving, ethics and integrity, commitment, self-control/work under pressure, relaxation, uncertainty, creativity, negotiation, emotional intelligence, commitment to the organization, reliability, attention to detail, delegation, search for information, analytical thinking, conceptual thinking, and flexibility. On the basis of a detailed PM literature review, Fisher (2011) highlighted that project managers need good and effective people skills, not only technical ability, to manage the people involved in their projects. On the basis of the results of his research, which aimed to identify the most important skills practitioners consider necessary in an effective project manager, the author identifies the following soft skills: managing the emotions, building trust, effective communication, motivating others, influencing others, cultural awareness when leading others, and team building. These types of soft skill are similar to what Pant and Baroudi (2008) highlighted on the basis of the literature analysis they present in their paper. With regard to the specific case of research projects, Ernø-Kjølhede et al. (2000) highlighted that PM requires two different kinds of skill. One is related to the "hard," or technical, side of project management (e.g. scheduling, planning, and controlling). The other is related to the "human processes", the "soft" side of project management. In this respect, the author identifies teambuilding, communication, and leadership as the main soft skills for project management.

Summarizing the literature mentioned above, it appears that in "hard projects," where both goals and methods are clearly set out beforehand, project managers are more likely to activate "hard skills" (or "process competences"). Conversely, in "soft projects", where the goals and methods are partially unknown, it may be presumed that project managers will mostly rely on soft skills. The literature highlights the "central role" of leadership capabilities in relation to other soft skills. Pinto and Trailer (1998) highlight that the characteristics of an effective project leader include many soft skills such as problem solving, tolerance of ambiguity, flexible management style, effective communication, etc. Crawford (2005) also noted that the project managers leadership influences all the other soft skills. On the basis of an extensive analysis of the literature, Yang et al. (2011) found relationships between leadership on the one hand and team communication, collaboration, and cohesiveness on the other. Bass and Avolio (1994) and Yammarino et al. (1998) highlight that leadership increases team communication and cooperation. On the basis of their research and an extensive review of the literature, Higgs and Dulewicz (2003) identified fifteen leadership competencies that they clustered under three groups: *Intellectual, Managerial and Emotional.* Specifically, they identified competencies such as engaging communication, resource management, empowering, developing, and achieving among the managerial competencies. The authors also suggest that leadership competencies facilitate the implementation of a goal-oriented approach as well as meeting targets and project effectiveness. Research carried out by Müller and Turner (2007) shows that leadership skills influence a projects success, including its overall performance (functionality, budget and timing). The central role of leadership capability in research project management was also highlighted by Ernø-Kjølhede et al. (2000). According to the author, the project manager has only very little formal authority over the participants in R&D projects. Many of the participants may only be working on the project part time and may have many other constraints on their availability, making it even harder for the project manager to obtain commitment from them. But lack of authority is not necessarily a drawback in the management of research projects, given the conditions of research work and the skilled and independent-minded nature of researchers. What is more important for the success of a research project is the leadership capability of the PI, because leadership facilitates commitment, team building, and a common vision within the research team. Based on the above, we formulated the following hypotheses:

Hypothesis 1): *A high level of awareness of project goals and task to be done to accomplish the project goals influences the activation of competencies related to the use of PM methods by PIs in the Science Sector.*
Hypothesis 2): *A low degree of awareness of project goals and task to be done to reach the project goals influences the activation of leadership competencies of PIs in the Science Sector.*
Hypothesis 3): *Leadership competencies positively influence the other soft skills of PIs working in the Science Sector.*

2.2 The statistical methodology

The research hypotheses will be explored using SEM methodology. The primary goal is to determine and validate a proposed causal process and/or model that can be described by a path diagram (Wright, 1921). This consists of boxes to represent observed (or measured) variables and circles (to represent latent variables), which are connected by arrows or paths to define causal relationships in the model, and will be represented by regression coefficients. Typically, SEM consists of the *structural model* (also known as *inner model*) and the *measurement model* (also known as *outer model*): the former specifies the dependence relationships between the theoretical constructs or latent variables, whereas the latter specifies the relationships between the theoretical constructs and their indicators or measured variables. Figure 1 shows the following three blocks that describe the structural model of our theory:
Hypothesis 1: *Awareness* of project goals and task to be done to accomplish the project goals is considered as an independent variable to explain a set of dependent variables comprising *Time management, Scope Management, Cost Management,* and *Risk Management.*
Hypothesis 2: *Awareness* may influence *Leadership capabilities*
Hypothesis 3: *Leadership capabilities* explains a set of dependent variables comprising the *Research Team, Communication,* and *Effectiveness.*
Figure 1 also shows the assumed algebraic sign associated with each causal relationship that needs to be verified in our structural model, using the data observed in the field analysis. Section 3 describes the measurement model by identifying the suitable indicators to be related to each of the theoretical constructs in the three blocks. In this way, it will be possible to structure a questionnaire for the field study in order to measure these indicator variables.

SEM has become de rigueur in validating instruments and testing linkages between constructs (Gefen et al., 2000). It is worth to notice that there are two families of SEM techniques: covariance-based techniques, as represented by LInear Strcutural RELations of Jöreskog (1978) and the well known LISREL software (Jöreskog and Sörbom, 1989), and variance-based techniques, of which Partial Least Squares Path Modeling (PLS-PM) is the most prominent representative (Monecke and Leisch, 2012; Esposito Vinzi et al., 2010; Tenenhaus et al., 2005). Unlike the covariance-based approach to SEM, PLS-PM does not reproduce a sample covariance matrix. It is more oriented towards maximizing the amount of variance explained (prediction) rather than statistical accuracy of the

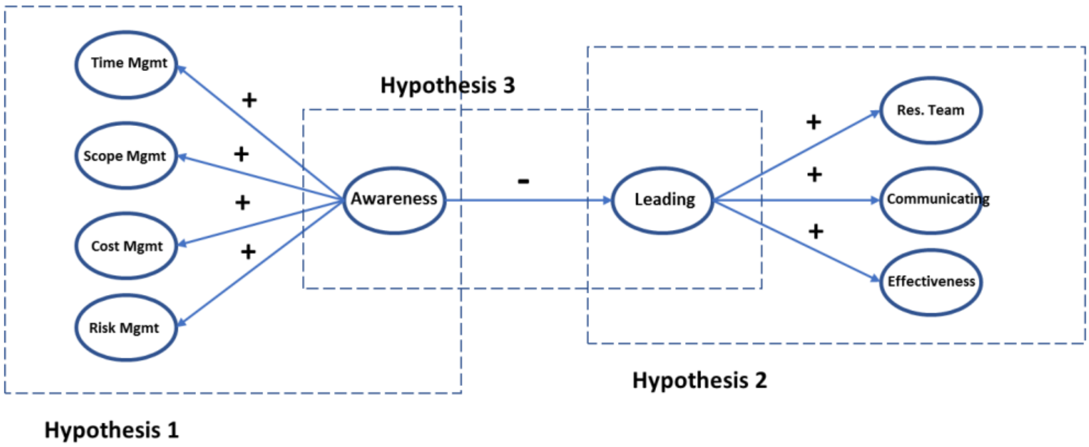

Figure 1: The causal relationships among the theoretical constructs in the research hypotheses and the control variables

estimates. An iterative least squares algorithm is used in alternating way to estimate, through simple or multiple linear regression, the measurement model and the structural model, therefore the procedures name is partial. There are many advantages to use PLS-PM instead of classical covariance-based estimation procedure: the PLS algorithm allows the unrestricted computation of cause-effect relationship models that employ both reflective and formative measurement models (Diamantopoulos and Winklhofer, 2001); PLS can be used to estimate path models when sample sizes are small (Esposito Vinzi et al., 2007); PLS path models can be very complex (i.e. consist of many latent and manifest variables) without leading to estimation problems (Wold, 1985). Furthermore, PLS path modeling can be used when distributions are highly skewed or when data are not normally distributed because the algorithm has no distributional requirements. Thus, PLS uses a soft modeling approach to SEM with no assumptions about data distribution (Esposito Vinzi et al., 2010). An additional approach to SEM is based on a semi-parametric estimator called *Generalized Maximum Entropy* (Ciavolino and Al-Nasser, 2009; Ciavolino and Dahlgaard, 2009; Bernardini Papalia and Ciavolino, 2011; Ciavolino et al., 2015; Ciavolino and Carpita, 2015; Carpita and Ciavolino, 2017). Recently, there are many applications of PLS-PM with several interesting issues (Ciavolino, 2017; Pelagatti et al., 2017; Simonetto, 2017; Bourini and Bourini, 2016; Ingusci et al., 2016; Bassi et al., 1978; Ciavolino et al., 2017).

3 The field study

3.1 The context of the research (CNR)

Our investigation was conducted within a public research institution, the National Research Council (CNR). It is the largest Italian public organization supporting scientific and technological research. It is supervised by the Ministry of Education, Universities and Research (MIUR). The institution was founded in 1923 and since then it has promoted and carried out research activities in pursuit of excellence and strategic relevance within the national and international spheres, in a framework of European cooperation and integration. It works in cooperation with academic research and with other private and public organizations, ensuring the nationwide dissemination of results. It promotes collaboration in the fields of science, technology and technical regulations with organizations and institutions from other countries and with supranational organizations in the context of extra-governmental agreements. Upon request from government authorities, it provides specific skills allowing Italy to participate in organizations or international scientific programs of an inter-governmental nature. The CNR has its own program of scholarships and research fellowships, educational and training activities in the form of Ph.D. courses, advanced post-graduate specialization courses, and programs of continuous or recurring education. It also provides technical and scientific support to the Public Administration when required (www.miur.it). The CNR can achieve its goals thanks to its 8,000 employees, 50% of whom are researchers and technologists. About 4,000 young researchers are engaged in postgraduate studies and research training at the CNR within the top-priority areas of interest. (www.cnr.it). The Scientific network of the CNR is organized into Departments and Research Institutes performing multidisciplinary activities. Departments are organizational units structured according to macro-areas of scientific and technological research. They mainly have planning, organizational, and supervision functions. The seven CNR Departments are as follows:

- Earth system science and environmental technologies
- Biology, agriculture and food sciences
- Chemical sciences and materials technology
- Physical sciences and technologies of matter
- Biomedical sciences
- Engineering, ICT and technologies for energy and transportation
- Social sciences and humanities, cultural heritage

The research institutes belonging to each department, gathered into several technical and scientific sectors, perform research tasks according to their programs. Their geographical distribution allows them to give a relevant contribution to both local and regional innovation. (www.cnr.it).

3.2 Sample selection

A field study on research project management competencies was conducted between August and September 2016 at the Biology, Agriculture and Food Sciences Department (DISBA) of the CNR. The department includes the following nine research institutes:

- Institute of plant genetics (IBBR)
- Institute of agricultural biology and biotechnology (IBBA)
- Institute for biometeorology (IBIMET)
- Institute of food sciences (ISA)
- Institute of sciences of food production (ISPA)
- Institute for Agricultural and Forest Systems in the Mediterranean (ISAFoM)
- Institute for the animal production system in the Mediterranean environment (ISPAAM)
- Institute for Sustainable Plant Protection (IPSP)
- Tree and timber institute (IVALSA)

DISBA provided a list of the research projects funded from 2013 to 2016. The list also included the name of the scientific advisor or PI for each project. It emerged that some researchers were responsible for more than one project over the period of interest. Thus, only one project was selected at random for each researcher yielding to 195 projects.

3.3 Data collection and measurement

On the basis of the results of the literature analysis in paragraph 2, we selected the skills that we felt had greater pertinence to the specific features of the research projects in order to define a list of competencies representative of public research organizations. The list includes competencies related to the use of both of the PM methods ("hard skills") and "soft skills." Based on this list, we developed a questionnaire used in a survey involving 195 PIs, namely those responsible for research projects at DISBA. The questionnaire comprised four sections:

1. the characteristics of the PI (age, sex, number of projects managed, experience and PM training)
2. the characteristics of the research project (project type, duration, budget, number of work units, number of researchers and research organizations involved, degree of detail regarding the project objectives and activities)
3. the process competencies of the PI
4. the personal competencies (soft skills) of the PI.

For the items in the first and second sections of the questionnaire we used closed questions assuming a set of pre-defined classes of values or categories. The items in the third section were measured using dummy variables (yes or no). The items in the fourth section were measured using a Likert scale (none, low, high, very high). As for the process competencies, we limited our attention to the application of knowledge and methods of a limited number of PM processes: *Time Management, Scope Management, Cost Management,* and *Risk Management.* This was because a previous study on the science sector shows that the spread of PM methodologies is somewhat limited due to a lack of knowledge, because the scientific advisor or PI prefers to focus on questions strictly related to the research itself rather than PM techniques (Ernø-Kjølhede et al., 2000; Kuchta et al., 2017). Concerning the block related to hypothesis 1, table 1 shows which indicators were taken into consideration for each theoretical construct as well as the specific questions used in the questionnaire. These variables refer to Awareness and the PM process competencies of the PI such as *Time, Scope, Cost and Risk Management.* Regarding

Table 1: Block relating to Hypothesis 1: awareness and list of process competencies

Construct	Indicator	Description
Awareness (AW)	AW1	Awareness and degree of detail of the research project objectives
	AW2	Degree of initial details of the activities to be undertaken (programming) in the research project
Time Management (TM)	TM1	I used specific techniques (e.g. using a Gantt chart, technical lattice, etc.) to plan the project activities
	TM2	I monitored the progress of the project by measuring, at fixed dates, the differences between the degree of programmed feed rate and the degree of actual progress of the project activities
Scope Management (SM)	SM1	I used technical specifications to define the project requirements (needs and expectations to be met)
	SM2	I used techniques to break down the specific development objectives of the project into different levels of activity (work breakdown structure) and I defined the project activities this way.
Cost Management (CM)	CM1	I used specific methods (based on analogies, parametric estimation, expert opinion, etc.) to plan the costs and define the budget of the project
	CM2	I monitored project costs by measuring, at fixed dates, the differences between the planned cost and the actual cost from the point of view of the activities implemented
Risk Management (RM)	RM1	During programming, I identified the likely risks with possible impact on the duration, costs and results of the project
	RM2	I evaluated the probability of risks and their impact on the duration, costs and results of the project
	RM3	I identified and implemented risk response measures

personal competencies, we produced a list of all the "soft skills" identified during the literature analysis (see section 2). Using this list, we set up a focus group with fifteen PIs from the CNR. Leveraging the experience and opinions of the researchers, we selected the following competencies as being the most representative of research PM: Leadership Capabilities, Effectiveness, Communication and Research Team Management. During the focus group meeting we also asked PIs to identify behavior indicators associated with each soft skill. Our specific aim was:

- to identify indicators of behavior that are specifically relevant to the scientific world, thus avoiding a generic description that would fail to take into account the peculiarity of the PM in specifically public research

- to share the terminology and the meaning of each indicator, thus limiting ambiguity in interpreting the individual questions. All these personal competencies became theoretical constructs in our theory.

Regarding the block relating to hypothesis 2, table 2 shows which indicators were considered for each theoretical construct. These variables refer to the personal PM competencies of the PI, namely the above-mentioned soft skills. At a second focus group meeting, the two lists of process competencies and personal competencies were revised, providing a description of the most significant indicators and choosing a suitable terminology before the questionnaire was submitted. In terms of leading, it should be noted that the

Table 2: Block relating to Hypothesis 2: list of personal competencies

Construct	Indicator	Description
Leading (LE)	LE1	I acted in such a way as to give support and advice in order to guide and improve the work of both individuals and teams
	LE2	Team members had confidence in me and asked me for advice and suggestions, especially in times of difficulty
	LE3	Team members took my suggestions into consideration
	LE4	I motivated and encouraged colleagues in the research team in the face of difficulties and problems
Research Team Management (RT)	RT1	I shared the definition of the project objectives with colleagues in the team
	RT2	I jointly and transparently defined the activities and responsibilities of colleagues in the team
	RT3	I was able to manage and resolve conflicts within the project team
Effectiveness (EF)	EF1	I endeavored to prevent rigidity and ensure flexibility in the project activities, all the while respecting the planned objectives
	EF2	I managed to solve the problems relating to the performance of the different project activities
	EF3	I was able to control the timing of the project activities
	EF4	I encouraged the creativity of the research team by stimulating the components to apply innovative methodological approaches
	EF5	Whilst sticking to the plan for the achievement of planned targets, I tried to ensure maximum flexibility in terms of management of the project activities by team members
	EF6	I was able to distinguish between the project phases that allowed room for creativity and innovation from the stages where respect for the activities as planned was more important.
Communicating (CO)	CO1	I listened attentively to provide team members with clear, up to date and timely information, and checked their understanding
	CO2	I facilitated and promoted communication among team members
	CO3	In all phases of the project, I took into account the expectations of all external stakeholders with regard to the team members and I used them as a benchmark when I had to review the planning of activities

indicators of behavior proposed by the Principal Investigators participating in the focus group that are specifically significant to the scientific world come under only one of the three leadership dimensions categories proposed by Higgs and Dulewicz (2003): "Managerial dimensions," while no indicator of behavior was proposed for the "Intellectual dimension" and "Emotional and social dimensions." In addition to the three hypotheses set out above, we consider two further latent variables, namely Size and Employment Level as *moderator variables* for the Leading variable. These will take into account the size of the project in terms of the total budget and the number of units and researchers involved; they may also consider the curriculum vitae and the experience of the PI. In addition to the above-mentioned hypotheses, we wished to verify whether Leading may depend on the size of the project and the curriculum vitae of the PI. The description of the indicator variables are in table 3. Indeed, it would be interesting to verify their main effects as well as their interactions with *Awereness* on *Leading*. A questionnaire was

Table 3: Moderator variables

Construct	Indicator	Description
Employment level (EL)	EL1	Coordinators career level within the CNR
Size (SZ)	SZ1	Number of resources available for the project
	SZ2	Number of researchers involved in the project
	SZ3	Number of research bodies involved in the project
	SZ4	Duration of the project
	SZ5	Total number of resources managed

drafted and submitted to the scientific advisor or PI of the 195 projects identified. The questionnaire was made up of 48 questions and was loaded on the web platform of the CNRs central training office. Each PI of each of the 195 projects selected was invited to complete the questionnaire in an e-mail sent by the head of training for the department under study. The decision to load the questionnaire on the CNR software platform was to guarantee the respondent's identity and to allow some information about employment level, workplace, etc. to be preloaded. The software platform also guaranteed the absence of detection errors and missing data.

3.4 The measurement models

PLS-PM includes two different kinds of measurement models, namely *reflective* or *formative*, and the selection of one rather than the other is subject to theoretical reasoning. The mode chosen indicates the direction of causality between the constructs and the indicators. In the reflective mode the co-variation among indicators is caused by, and therefore reflects, variation in the underlying latent factor. This is the case of all constructs included in the three blocks of the three hypotheses except for the *Awareness* construct in figure 1. Thus, it is hypothesized that changes in the underlying construct will cause changes to the indicators, so the measures are referred to as reflective or effects indicators (Jarvis et al., 2003). Reflective indicators of a latent construct should be internally consistent and, because all the measures are assumed to be equally valid indicators of the underlying construct, any two measures that are equally reliable are interchangeable. In the formative mode, it is hypothesized that changes to the indicators will cause changes in the underlying construct. This approach assumes that all measures have an impact (or a causal link) on a single construct. This is the case of indicators explaining the *Awareness*.

3.5 Sample characteristics

The questionnaire was submitted to 195 PIs at the CNR, but only 80 answered all sections and were thus considered for the final analysis. Table 4 describes the frequency distributions of the features relating to the characteristics of the respondents and the projects studied. 57.5% of the respondents were men, 58.8% aged over 50, 45.0% (25.0%+20.0%) had managed more than three research projects in their career, 3.7% had certified knowledge of project management, while 7.5% had attended training courses in project management. Regarding the characteristics of the research projects selected, 96% were found to have well-defined objectives, 93% had very detailed activities in the planning stage (4), and 63.7% (36.3+27.4) involved managing more than €100,000. 71.3% (60.0+11.3) of the projects had a duration of more than 3 years, and 53.7% (60.0+11.3) involved more than three research institutions.

4 Results

4.1 Project Management competencies of Principle Investigators

The PIs' answers in our sample as shown in table 5 indicate an emphasis on high and very high degrees of awareness of both aspects project goals and methods. This confirms our assumption as described in section 2 that Turner and Cochrane (1993) classification into just two classes of "poorly defined" and "well defined" projects is not necessarily true.

Concerning PI process competencies, there is limited use of tools and methods for defining scope (only 53.1% of our sample answered "yes") or for monitoring costs (only 43.1% of our sample answer "yes"). On the other hand, there is great attention to time management (72.5% of our sample answered "yes") and risk management (62.5% of our sample answered "yes"). These results are shown in figure 2. Such findings are different from those obtained in the study conducted by Kuchta et al. (2017) in Poland. These authors found PIs paid limited attention to process competencies, especially time management. In fact, our field study reveals that the use of time management methods has become necessary in public sector projects because they are often funded by the European Commission or other institutions, and they are very strict in relation to respecting project scheduling. They require the submission of administrative and scientific reports at the due time in order to ensure payments. The assessment of the personal competencies of PIs was carried out using a Likert scale with four values (none, low, high, very high). Figure 2 shows the results.

4.2 PLS path estimation and model assessment

The analysis was performed using PLS-SEM toolbox 2.4 (Aria, 2015), developed in Matlab/Octave and freely available from the Matlab File Exchange repository. The PLS-PM structural model is used with a path-weighting scheme where the relationships between the latent variables are specified as direct (Lohmöller, 1989). Model assessment

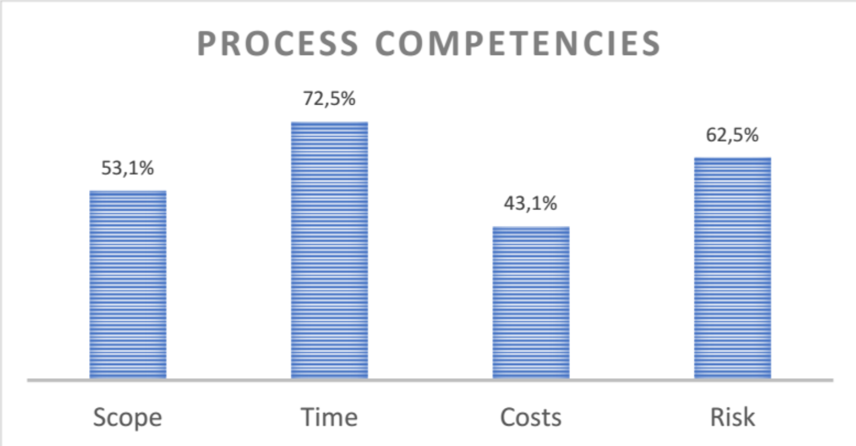

Figure 2: The presence of process competencies

consists of two main steps: the assessment of the structural or inner model and the assessment of the measurement or outer model.

4.2.1 Assessment of the inner model

Figure 4 shows the estimation of the path coefficients and the model fit of the structural model. The individual path coefficients can be interpreted as linear bivariate correlation coefficients, which are equivalent to the standardized beta coefficients of ordinary least square regressions. The essential criterion for structural or inner model assessment is the coefficient of determination R^2 of the dependent or endogenous latent variables. Chin (1998) describes R^2 values of 0.67, 0.33, and 0.19 in PLS path models as substantial, moderate, and weak respectively. If certain inner path model structures explain an endogenous latent variable by only a few (e.g., one or two) independent or exogenous latent variables, "moderate" R^2 may be acceptable. Table 6 shows R^2 values for all endogenous latent variables. Two constructs, "Leading" and "Risk Management," return weak values. Table 7 shows statistical testing on the path coefficients for Direct Effects. P-value ≤ 0.05 implies that a coefficient is significantly different from 0. Structural paths, whose sign is in keeping with *a priori* postulated algebraic signs, provide a partial empirical validation of the theoretically assumed relationships between latent variables. Paths that possess an algebraic sign contrary to expectations do not support the a *priori* formed hypotheses. Confidence intervals and p-values for path coefficients were obtained using the bootstrap resampling technique (Tenenhaus et al., 2005) in order to determine the statistical significance of the results. In our results, all signs match the first and third hypotheses of our research whereas the second hypothesis is not verified. Thus, *Awareness* of the project goals and the tasks to be done determines positive activation of *"hard skills"* in the PI in terms of *Time Management* (with path coefficient of 0.282), *Scope*

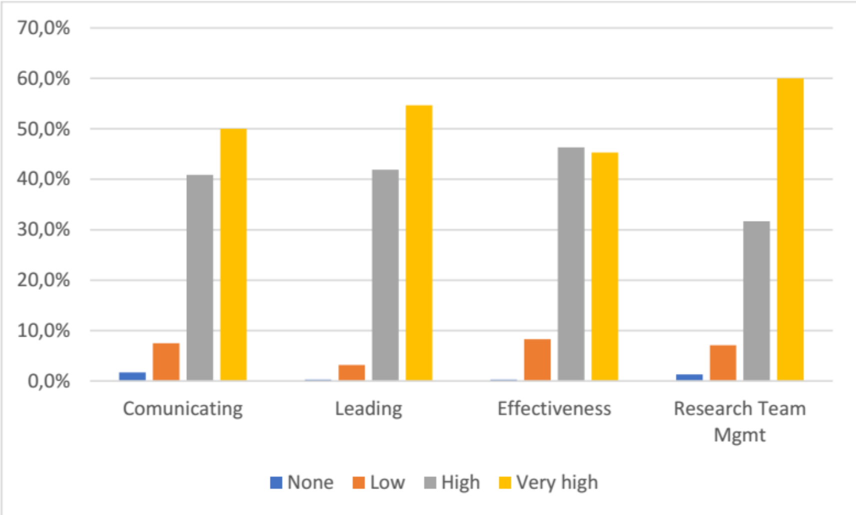

Figure 3: The degree of personal competencies

Management (with path coefficient of 0.240), *Cost Management* (with path coefficient of 0.257), and *Risk Management* (with path coefficient 0.351). Even higher impact shows *Leadership capabilities* tending toward the activation of "soft skills" such as *Research Team Management* (with path coefficient 0.605), *Communication* (with path coefficient 0.681) and *Effectiveness* (with path coefficient 0.654). The results concerning *"Leadership capabilities"* are confirmed by higher path coefficient p-values. On the other hand, the moderator variables *"Size"* and *"Employment Level"* as well as their interactions with *Awareness* have no significant effect on *"Leadership capabilities." Awareness* has a positive rather than a negative impact on *Leading*. For each relationship between two latent variables, it is also possible to evaluate the presence and the measure of indirect effects (Table 8). This is the measure of the relationship between two constructs that are indirectly connected to each other. There are three significant indirect effects in our research: *"Awareness"* affects *"Research Team Management," "Communication,"* and *"Effectiveness."*

4.2.2 Assessment of the outer model

The measurement models were assessed for reliability and validity, and the results are shown in table 9. The first criterion to be checked is usually the reliability of internal consistency. The traditional criterion for internal consistency is Cronbach's α (Cronbach, 1951), which provides an estimate for reliability based on indicator inter-correlations. In PLS path modeling, Cronbach's α is characterized by a severe underestimation of the internal consistency reliability of a reflective construct. Hence, it is more appropriate to apply two different measures of composite reliability: Jöreskog's ρ_c (Werts et al., 1974) and Dijkstra-Henseler's ρ_a (Dijkstra and Henseler, 2015). An internal consistency relia-

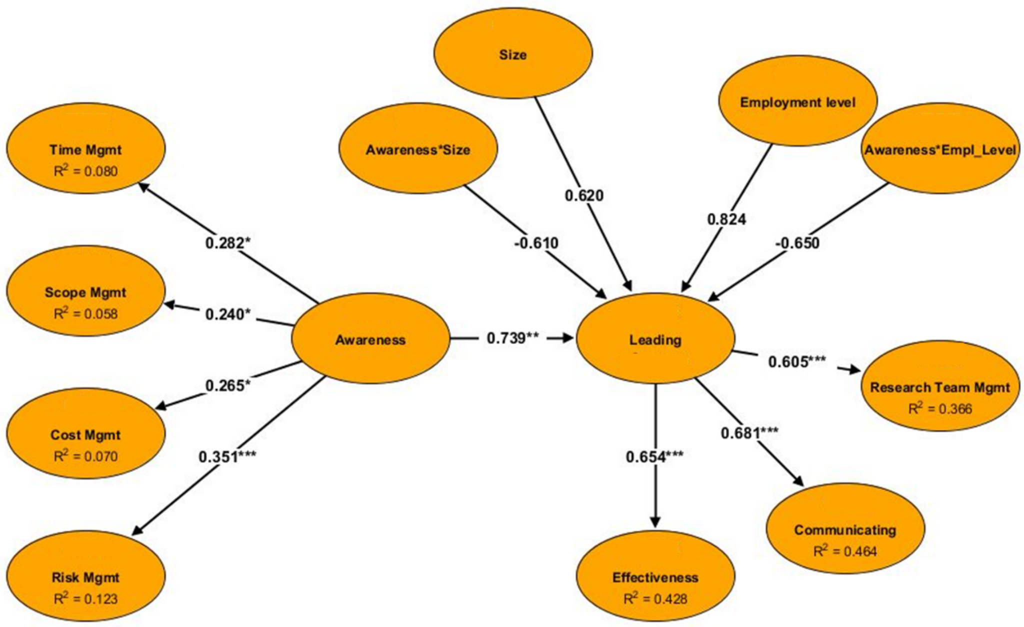

Figure 4: Structural Model estimation

bility value greater than 0.7 in the early stages of research and values greater than 0.8 or 0.9 in more advanced stages of research are considered satisfactory (Henseler et al., 2016), whereas a value below 0.6 indicates lack of reliability. Composite reliability and Cronbach's α values confirm good internal consistency for all constructs. Some authors recommend eliminating reflective indicators with a loading less than 0.4. In taking into account the characteristics of PLS it only makes sense to discard an indicator if it has low reliability, and if eliminating it will lead to a substantial increase in composite reliability. To assess validity, two complementary aspects are normally considered: convergent validity and discriminant validity. Convergent validity means that a set of indicators represents one and the same underlying construct. Fornell and Larcker (1981) suggest using the Average Variance Extracted (AVE) as a criterion for convergent validity. An AVE value of at least 0.5 indicates sufficient convergent validity, meaning that a latent variable is able to explain more than half of the variance of its indicators on average. The results in table 7 confirm a good convergent validity with all values close to or higher than 0.5 except for the control variables. Discriminant validity implies that the joint set of all indicators is expected not to be uni-dimensional. In PLS, this aspect is evaluated by means of three measures:

1. the Fornell and Larcker criterion
2. the Heterotrait-monotrait (HTMT) ratio of correlations
3. cross-loading.

The first one states that a construct has to explain more variance with its indicators than with the other latent variables. In statistical terms, this means that the AVE of a construct should be greater than the latent variables highest squared correlation with any other latent variable. The second criterion measures validity as the ratio between the heterotrait correlation (HT, the average correlations of indicators across constructs measuring different phenomena) and the monotrait correlations (MT, the correlations of indicators within the same construct) for each construct (Henseler et al., 2016). The authors suggested a ceiling value of 0.90. The third criterion implies that the loading of each indicator is expected to be greater than all of its cross-loadings (Chin, 1998). Table 10, table 11, table 12 show the results for the three criteria. Following the Fornell and Larcker approach, all constructs satisfy the criterion, while for the HTMT, only *Leading* against *Communicating* and *Effectiveness* has a value falling below the threshold. Looking at cross-loadings results, the criterion is met by all indicators.

5 Discussion of the results and concluding remarks

Our study aimed to contribute to a topic that is still largely unexplored in the literature, namely the diffusion of Project Management competencies in the Science Sector of public research. As Kuchta et al. (2017) point out, studies on R&D projects tend to cover the industry sector rather than research projects financed by public funds at national laboratories and research institutes. In the relevant literature there is practically no quantitative research characterizing R&D project management in the science sector. Furthermore, no study has ever addressed the topic of the diffusion of PM approaches and competencies in Italy. Our study highlighted poor levels of Principal Investigators participation in Project Management training initiatives (7.5%), and extremely limited certification of PM skills, at barely 3.7%. Investment in PM training in public sector research centers thus appears very limited. This could be indicative of the limited sensibility of Senior Management to Project Management training, which is, however, an area requiring greater study. Despite limited recourse to PM training, attention to process competencies is fairly widespread, as 72.50% of those interviewed claimed to use methodological tools for project time management, and 62.5% state that they use tools to manage risk. Tools and methods to define scope (53.31%) and costs (43.13%) are used less frequently. It may be concluded that a PIs knowledge of methods connected with PM process competencies is the result of self-instruction and learning from experience in the field. We consider this to be a very important aspect because where recourse to process competencies highlights the necessity PIs have to use support methodologies to manage scope, time, costs, and risk in the research projects in their care, no elements are present from which it is possible to assess to what extent the use of PM methods is supported by adequate and up-to-date knowledge, as this develops only through self-instruction and experience in the field. This raises some issues regarding the appropriate use of PM techniques and the actual contribution of these techniques to the effective management of the research program. The results relating to the diffusion of process competencies among PIs partially contrast with those carried out in the public research sector by Kuchta et al. (2017) in Poland, which we believe to be the only study on this subject in the public research sector. The authors found that project managers paid little attention to process competencies, and especially made very limited use of time monitoring methodologies. In our case, the widespread use of time management techniques may be due to the fact that most of the research projects making up the survey were funded by the European Union or other bodies and are subject to strict schedules imposed by those providing the funding, who set strict and inflexible deadlines for the presentation of scientific and administrative reports.

Another of our findings that we consider worthy of note is the degree of (initial) knowledge by those in charge of the projects making up the sample with regard to the goals of the project and the tasks to be done. Both factors are widely distributed between "medium-low" and "high." The results of our research do not coincide with Turner and Cochrane (1993) conclusion that research projects typically have neither well defined goals nor well defined methods. On the other hand, there are some substantial similarities to the previously mentioned study of 2015 carried out in the context of Polish public research by Kuchta et al., a context very similar to the one in this study. Their study too, using a sample of over 1000 projects, showed variation in the degree of awareness of the goals of the project and the tasks to be done. From the results of the Polish and Italian studies, we can state that projects centering on public research can have the characteristics of "hard projects" and "soft projects," to use the classification devised by Crawford and Pollack (2004). On the other hand, Crawford and Polland, like the previous authors (Turner and Cochrane, 1993), (only) considered "soft projects." A possible explanation for this difference is that these authors focused on R&D projects that had mainly been designed for the industrial sector, with very high costs and levels of complexity, innovation, and thus uncertainty. Conversely, the projects featuring in our study and in the other work mentioned above revealed differing levels of complexity, innovation and costs.

Moving on to the statistical analysis of the findings (see section 4.2), the first and third hypotheses of our research are confirmed.

Hypothesis 1): High levels of awareness of project goals and the task to be done to reach project goals influence the activation of competencies related to the use of project management methods by Principal Investigators working in the Science Sector

Hypothesis 3): In the category of soft skills, leadership capabilities positively influence other soft skills among the Principal Investigators within the science sector.

The second hypothesis is not confirmed. Hypothesis 2): a low degree of awareness of project goals and task to be done to reach the project goals influences the activation of leadership capabilities in PIs. This result is the opposite of what appears in the literature, namely that in the case of "soft projects," uncertainty in terms of both objectives and working methods makes it difficult to plan and monitor with any precision. The project managers "soft skills" (such as problem solving, tolerance for ambiguity, flexible management style, effective communication, etc.) outweigh the "hard skills," and leadership capabilities play a significant role in the soft skills, and it is these that allow the project manager to maintain cohesion and team spirit among the project team even in moments of uncertainty and difficulty. From our sample of Principal Investigators, it has emerged that a high level of awareness of the project objectives and tasks to be done positively influences the activation of both the process, or "hard" skills and leadership and other "soft" skills. The PIs in our sample therefore feel that they are more likely to be listened to and heeded by members of the research team, and their suggestions to be followed, when the goals and working methods of the project are well defined. When these are ill defined, they are less able to exercise their skills. A possible interpretation of this finding may be that in several cases the PI may have little official authority over the participants in the project, who, as peers, are not subordinated to him or her (Ernø-Kjølhede et al., 2000). In some circumstances this may make it harder for a PI to obtain commitment from participants in conditions of uncertainty in terms of objectives and working methods. Conversely, when the goals and working methods are well defined, uncertainties are reduced, and this may make it easier for the PI to obtain a greater level of commitment from the participants despite not having a higher rank in the hierarchy. We consider confirmation of the third hypothesis important because it shows that (also) in public research, the leadership capabilities of the project managers form a central element in the management of both the project and the group. The results from the estimation obtained using the structural model showed the strong influence of Leadership Capabilities on Effectiveness, Communication and Research Team Management Competencies. Based on the description of the behavior descriptors for the various soft skills (see list of personal skills shown in section 3) it is possible to illustrate better the relationship between Leadership Capabilities and the other soft skills. Our study particularly highlights how the Leadership capability of a research group manager

- facilitates, from the perspective of *research group management*, project objective sharing between the manager and other researchers, the process of subdividing activities and responsibilities among the project members by the manager, and conflict management within the research group
- has a positive influence, from the *perspective of the effectiveness of project management*, on the ability to foster creativity in members of the research team, solving problems relating to the various activities, providing flexibility for project management, alternating, as necessary, phases with less rigid time and performance control and greater emphasis on creativity and innovation with phases that lay greater emphasis on timing and the results of scheduled activities
- in terms of communication skills, it positively influences the effectiveness of communication by the research project manager with the members of the research team and the projects external stakeholders.

The results from the estimation obtained using the structural model also show that the leadership capability of research project managers is not influenced by the size of the project nor by the research group manager's status (researcher or senior manager). This result is reflected in the characteristics of the research institute itself, such as the lack of hierarchy, the fact that informal organizational variables prevail over formal ones, and the scientific weight of the researchers regardless of the levels of official authority (Ernø-Kjølhede et al., 2000). The centrality of Leadership Capabilities compared with other types of soft skills in public research is, in our opinion, a significant finding. We believe that the role of soft skills in managing public research projects by PIs has not yet been addressed in literature, despite the fact that in other related fields, such as R&D, literature has highlighted the central role of soft skills and leadership, especially in contributing to the success of projects in the private industry and high tech sectors. We therefore believe that the hypothesis of the centrality of leadership capability compared with the other soft skills of the PI of research projects is a significant result and should be explored further in order to identify which specific dimensions of leadership skills compared to those highlighted in the literature are more suited to the specific professional figure under study. These findings may also be able to highlight suitable training activities and individual development work able to reinforce this skill.

A CNR department is basically an aggregation of institutes working on similar research topics. In our study, investigating the PM competencies of PIs in only one CNR department, we conducted an analysis limited to a homogeneous typology of research project in terms of topics. However, the PM competencies of the PI may vary with the research topic. Extending the analysis of the PM competencies of the PI to all the CNRs departments, dealing with different research topics, could better define the phenomena under study and make it possible to test the hypotheses using a larger and more representative sample, thus overcoming some limits of our study: no pre-established list of the projects and therefore of the PIs to be analyzed would be drawn up; each PI would independently identify a project to be used for the analysis.

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Table 4: Sample characteristics

Characteristics of respondents	**Responses**	**Occurrences**	**%**
Age (in years)	- From 31 to 40	6	7.5
	- From 41 to 50	27	33.8
	- Over 50	47	58.8
Gender	- Male	46	57.5
	- Female	34	42.5
Employment level	- Director of research	28	35.0
	- Researcher	52	65.0
N. of projects	- 1 project	23	28.7
	- 2 or 3 projects	21	26.3
	- From 4 to 6 projects	20	25.0
	- Over 6 projects	16	20.0
Certified Project Management competencies	- No	77	96.3
	- Yes	3	3.7
Project Management courses attended	- No	74	92.5
	- Yes	6	7.5
Characteristics of the projects considered	**Responses**	**Occurrences**	**%**
Project type	- Regional	16	20.0
	- National	19	23.8
	- European	19	23.8
	- International	24	30.0
	- Other	2	2.4
Budget	- Up to €100k	29	36.3
	- From €101k to €500k	29	36.3
	- Over €500k	22	27.4
N. of researchers	- Up to 2	23	28.7
	- From 3 to 6	35	43.8
	- More than 6	22	27.5
N. of workers	- Up to 4	27	33.8
	- From 5 to 10	34	42.4
	- More than 10	19	23.8
N. of partners	- Up to 2	37	46.3
	- From 3 to 6	25	31.3
	- More than 6	18	22.4
Project duration	- 1 or 2 years	23	28.7
	- 3 or 4 years	48	60.0
	- Over 4 years	9	11.3

Table 5: Level of Awareness of project goals and tasks to be done

	Awareness of project goals	*Awareness of tasks to be done*
None	0.0%	0.0%
Low	7.5%	3.8%
High	56.3%	50%
Very High	36.3%	46.3%

Table 6: Structural model assessment: R Squares

Independent variables	**Dependent variable**	**R Square**	**Strength**
Leading	→ *Research Team Mgmt*	0.366	Moderate
Awareness, Size, Employment level. AwarenessXSize, AwarenessXEmployment level	→ *Leadership capabilities*	0.269	Weak
Leading	→ *Communication*	0.464	Moderate
Leading	→ *Effectiveness*	0.428	Moderate
Awareness	→ *Scope Mgmt*	0.058	Low
Awareness	→ *Time Mgmt*	0.080	Low
Awareness	→ *Cost Mgmt*	0.070	Low
Awareness	→ *Risk Mgmt*	0.132	Weak

Table 7: Structural model assessment: *Direct Effects*

Research Hypo.	**Direct effects**	**Path coefficients**	**T stat**	**Pvalue**		**Bootstrap 95% CI**	
H2	*Leadership capabilities → Research Team Mgmt*	0.605	8.403	< 0.001	***	0.449	0.729
H2	*Leadership capabilities → Communication*	0.681	11.353	< 0.001	***	0.560	0.803
H2	*Leadership capabilities → Effectiveness*	0.655	10.049	< 0.001	***	0.543	0.797
H3	*Awareness → Leadership capabilities*	0.739	3.176	< 0.001	***	0.154	1.000
H1	*Awareness →Scope Mgmt*	0.240	2.213	0.027	*	0.057	0.465
H1	*Awareness → Time Mgmt*	0.282	2.310	0.021	*	0.074	0.499
H1	*Awareness → Cost Mgmt*	0.265	2.452	0.014	*	0.051	0.471
H1	*Awareness → Risk Mgmt*	0.351	3.954	< 0.001	***	0.213	0.534
Control	*Size → Leading*	0.620	0.977	0.329		-0.948	1.265
Control	*AwarenessXSize → Leading*	-0.610	-1.355	0.176		-1.374	0.419
Control	*Employment level → Leading*	0.824	1.066	0.287		-0.884	2.103
Control	*AwarenessXEmployment level → Leading*	-0.650	-0.878	0.380		-1.884	0.968

* indicates that a direct effect between the two constructs is significant (Pvalue $\leq$ 0.05.) or *** (Pvalue $\leq$ 0.01) using bootstrap procedure with 1000 replications.

Table 8: Structural model assessment: *Indirect Effects*

Indirect effects	**Path coefficients**	**T stat**	**Pvalue**		**Bootstrap 95% CI**	
Awareness → Research Team Mgmt	0.447	2.836	0.004	***	0.093	0.684
Awareness → Communicating	0.503	2.994	< 0.002	***	0.100	0.774
Awareness → Effectiveness	0.483	3.196	< 0.001	***	0.108	0.700
Size → Research Team Mgmt	0.375	0.947	0.344		-0.598	0.810
Size → Communicating	0.422	0.971	0.331		-0.647	0.868
Size → Effectiveness	0.405	0.940	0.347		-0.658	0.891
Employment level → Research Team	0.497	1.063	0.288		-0.577	1.304
Employment level → Communicating	0.561	1.033	0.302		-0.581	1.535
Employment level → Effectiveness	0.539	1.050	0.294		-0.646	1.380

* indicates that a direct effect between the two constructs is significant (Pvalue $\leq$ 0.05.) or *** (Pvalue $\leq$ 0.01) using bootstrap procedure with 1000 replications.

Table 9: Assessment of the measurement model: construct reliability and validity

Construct	Measurement model	Cronbach α	Jöreskog's rho (ρ_c)	Dijkstra-Henseler's rho (ρ_a)	Average Variance Extracted (AVE)
AW	Reflective	0.658	0.852	0.686	0.743
TM	Reflective	0.612	0.692	1.134	0.567
SM	Reflective	0.660	0.790	0.670	0.653
CM	Single indicator	—	—	—	—
RM	Reflective	0.742	0.841	0.895	0.643
LE	Reflective	0.732	0.832	0.738	0.555
RT	Reflective	0.609	0.789	0.610	0.553
EF	Reflective	0.650	0.773	0.698	0.573
CO	Reflective	0.672	0.773	0.675	0.546
EL	Single indicator	—	—	—	—
SZ	Reflective	0.768	0.806	0.553	0.493

Table 10: Discriminant validity (Fornell and Larcker criterion). Squared bivariate correlations between constructs

Construct	RT	LE	CO	EF	AW	SZ	EL	SM	TM	CM	RM
RT	0.553										
LE	0.370	0.555									
CO	0.263	0.465	0.546								
EF	0.228	0.431	0.218	0.573							
AW	0.062	0.174	0.048	0.050	0.743						
SZ	0.036	0.058	0.004	0.024	0.045	0.493					
EL	0.015	0.027	0.020	0.006	0.002	0.068	—				
SM	0.004	0.010	0.015	0.000	0.067	0.003	0.025	0.653			
TM	0.001	0.008	0.001	0.003	0.087	0.112	0.000	0.116	0.567		
CM	0.052	0.078	0.050	0.101	0.066	0.169	0.036	0.037	0.208	—	
RM	0.001	0.012	0.007	0.034	0.134	0.067	0.010	0.040	0.159	0.135	0.643

Diagonal elements represent AVE. * indicates a squared correlation not satisfying the FL criterion

Table 11: Discriminant validity. Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	RT	LE	CO	EF	SZ	EL	SM	TM	CM
RT									
LE	0.869								
CO	0.830	0.909*							
EF	0.730	0.919*	0.776						
SZ	0.167	0.196	0.013	0.123					
EL	0.156	0.202	0.183	0.130	0.344				
SM	0.127	0.165	0.241	0.002	0.134	0.227			
TM	0.010	0.084	0.090	0.012	0.582	0.026	1.050*		
CM	0.313	0.334	0.283	0.347	0.452	0.189	0.284	0.674	
RM	0.073	0.154	0.080	0.197	0.297	0.093	0.316	0.654	0.404

* indicates a ratio not satisfying the HTMT criterion.

Table 12: Discriminant validity (cross loadings criterion). Loadings (in bold font) and cross loadings (in normal font)

	Construct										
Item	AW	CM	CO	EF	EL	LE	RM	RT	SM	SZ	TM
AW1	**0.946**	0.223	0.183	0.160	-0.041	0.367	0.367	0.190	0.271	0.249	0.285
AW2	**0.711**	0.231	0.213	0.284	-0.046	0.362	0.210	0.289	0.119	0.037	0.192
CM1	0.254	**1.000**	0.221	0.314	0.187	0.276	0.363	0.224	0.191	0.406	0.450
CO1	0.214	0.223	**0.804**	0.356	0.106	0.487	0.144	0.307	-0.029	0.124	0.004
CO2	0.198	0.179	**0.858**	0.374	0.125	0.642	0.054	0.529	-0.129	0.040	0.036
CO3	0.014	0.061	**0.464**	0.304	0.069	0.293	-0.058	0.218	-0.116	-0.052	-0.180
EF1	0.268	0.353	0.353	**0.762**	-0.008	0.552	0.194	0.464	-0.002	0.255	0.057
EF2	0.203	0.304	0.301	**0.681**	0.011	0.472	0.140	0.284	0.011	0.042	0.117
EF3	0.096	0.167	0.192	**0.522**	0.036	0.297	0.203	0.318	0.105	0.067	0.148
EF4	0.065	0.033	0.276	**0.359**	0.208	0.253	0.031	0.235	-0.081	0.027	-0.135
EF5	0.039	-0.014	0.262	**0.582**	0.077	0.328	0.114	0.158	-0.065	0.000	-0.100
EF6	0.041	0.158	0.293	**0.628**	0.049	0.378	-0.046	0.214	0.027	0.083	0.034
EL1	-0.048	0.187	0.139	0.076	**1.000**	0.163	0.093	0.119	-0.154	0.257	0.017
LE1	0.268	0.268	0.449	0.390	0.211	**0.670**	0.119	0.276	-0.084	0.259	0.085
LE2	0.336	0.198	0.512	0.590	-0.057	**0.736**	0.028	0.483	-0.036	0.105	0.155
LE3	0.286	0.139	0.539	0.495	0.180	**0.776**	0.065	0.504	-0.135	0.153	-0.037
LE4	0.333	0.234	0.501	0.442	0.173	**0.755**	0.122	0.497	-0.034	0.213	0.061
RM1	0.391	0.333	0.102	0.168	0.099	0.077	**0.894**	-0.014	0.221	0.247	0.402
RM2	0.254	0.325	0.050	0.228	0.081	0.134	**0.818**	0.050	0.096	0.173	0.260
RM3	0.137	0.180	0.000	-0.035	0.013	0.051	**0.641**	-0.156	0.131	0.191	0.247
RT1	0.194	0.302	0.427	0.295	0.111	0.388	0.006	**0.734**	0.073	0.188	-0.001
RT2	0.188	0.182	0.348	0.340	0.082	0.389	-0.015	**0.731**	0.078	0.245	-0.044
RT3	0.172	0.058	0.362	0.401	0.077	0.533	-0.032	**0.741**	-0.004	0.025	0.089
SM1	0.208	0.043	-0.213	-0.017	-0.187	-0.193	0.132	-0.042	**0.803**	-0.035	0.184
SM2	0.204	0.268	0.022	0.021	-0.061	0.040	0.188	0.138	**0.794**	0.124	0.361
SZ1	0.153	0.446	-0.014	0.092	0.178	0.021	0.275	0.007	0.184	**0.697**	0.408
SZ2	0.175	0.220	0.003	0.046	0.254	0.118	0.119	0.086	0.063	**0.744**	0.195
SZ3	0.132	0.321	0.023	0.111	0.151	0.182	0.141	0.201	-0.055	**0.598**	0.191
SZ4	-0.040	0.133	-0.092	-0.006	0.294	-0.023	0.008	-0.039	-0.003	**0.454**	0.123
SZ5	0.142	0.290	0.087	0.141	0.200	0.198	0.243	0.103	0.093	**0.808**	0.289
TM1	0.059	0.211	0.003	-0.050	0.008	-0.034	0.144	-0.020	0.413	0.179	**0.404**
TM2	0.297	0.438	-0.028	0.067	0.017	0.099	0.390	0.037	0.276	0.316	**0.971**

* indicates a ratio not satisfying the cross loadings criterion.