Received 17 September 2023
Revised 14 January 2024
7 August 2024
8 May 2025
Accepted 6 July 2025

Risks of funding innovation in public policies

Samuel Façanha Câmara and José Glauco Paula Pinto
Department of Postgraduate Program in Administration, Universidade Estadual do Ceara, Fortaleza, Brazil

Elias Pereira Lopes Júnior
Department of Postgraduate Program in Administration, Universidade Federal do Cariri, Juazeiro do Norte, Brazil

Jorge Barbosa Soares
Department of Engineering, Universidade Federal do Ceara, Fortaleza, Brazil, and

Eufrasina Campelo Borges Mendonça Barbosa
Department of Innovation, Fundação Cearense de Apoio ao Desenvolvimento Científico e Tecnológico, Fortaleza, Brazil

Abstract

Purpose – While the financing sources available in the market do not provide sufficient financial support for the establishment of companies with high innovative impact, the public sector financing sources play an effective role in granting non-reimbursable resources to these companies, especially during the initial phases that involve greater risks in innovation. This study aims to construct a risk estimation model for subsidized financing of innovation-promoting organizations in emerging economy countries.

Design/methodology/approach – A database was used with historical data of 77 projects submitted to public notices to promote innovation from a promoting organization. The analyses were conducted using the technique of discriminant analysis and three risk models were considered in the analysis.

Findings – It was evident that, the more the benefited project teams have high academic qualification (Human Capital) and the more these same teams are socially integrated within a closed cohesive structure (Clustering Social Capital), greater are its innovative qualities and lower are the levels of technological and management risk associated with the economic subsidy program. This study demonstrates that a risk prediction tool can contribute to the local economic subsidy program by signaling the need for actions to be taken during the project selection phase for funding.

Originality/value – The main contribution of this paper is the proposal and construction of an important tool for use in risk perception and aid in fund decision-making public financing for business innovation projects, proposing a risk management tool with a reasonable degree of assertiveness.

Keywords Innovation public funding, Technological and management risks, Human Capital, Social Capital, Technology Readiness Level – TRL

Paper type Research paper

Asia Pacific Journal of Innovation and Entrepreneurship
Vol. 19 No. 4, 2025
pp. 378-397
Emerald Publishing Limited
e-ISSN: 2398-7812
p-ISSN: 2071-1395
DOI 10.1108/APJIE-09-2023-0170

1. Introduction

Research on public policies aimed at fostering innovation and the role of promoting organizations has advanced significantly, with emphasis on the diverse formats these policies take (Corder and Salles Filho, 2006; Borrás and Edquist, 2013; Dumont, 2017; Falk and Svensson, 2020; Fiorentin *et al.*, 2023). Studies have also explored the impacts of such policies on beneficiary firms and on the broader innovation and entrepreneurship ecosystems in specific regions and countries (Lepori *et al.*, 2007; Blanes and Busom, 2004; Cannone and Ughetto, 2014; Berrutti and Bianchi, 2020; Rosário *et al.*, 2022; Buarque *et al.*, 2023). Promoting organizations are understood as institutions that play a pivotal role in financing high-risk, early-stage innovation projects, serving as catalysts for technological development and economic transformation.

Another line of research compares different innovation incentive models—such as grants, subsidies, training programs and access to customer and investor networks (Wainova, 2009; Wu *et al.*, 2021). However, there remains a significant gap in the literature regarding the implementation of these policies from the perspective of the promoting organizations themselves. Examining this perspective would offer valuable insights to support these institutions in their decision-making processes, particularly when evaluating and selecting among competing applications for innovation support.

Building on previous studies that have begun to explore this issue (Cannone and Ughetto, 2014; Fiorentin *et al.*, 2023), this research poses the following question:

RQ1. How can risk analysis be structured for organizations that promote public policies aimed at stimulating innovation, particularly in the selection of beneficiary companies?

This question gains relevance due to the scarcity of studies addressing this specific perspective and the critical need to better understand the criteria and decision-making processes involved in awarding innovation incentives to firms.

The context in which these selection decisions are made is shaped by the inherent uncertainties of the business innovation process (Smits and Kuhlmann, 2004; Lepori *et al.*, 2011; Del Río and Kiefer, 2022). These uncertainties include:

- the risk that the technology or innovative solution may not deliver the expected outcomes;
- the possibility that the development team may be unable to overcome the technical challenges involved;
- a lack of interest from potential or target customers in the proposed innovation; and
- delays in development that result in missed market opportunities, diminishing the innovation's potential to become a competitive differentiator.

These and other factors underscore the complexity of the innovation phenomenon in its many dimensions (Damanpour, 1996; McElroy, 2003; Antonelli, 2009; Poutanen *et al.*, 2016; Rhaiem and Amara, 2021).

Promoting organizations can attempt to anticipate which proposals for public innovation incentives carry higher levels of risk. By identifying and measuring these risks, they are better equipped to make informed decisions about which projects to include in their portfolios. This study seeks to contribute to this effort by offering a partial but meaningful analysis of these challenges, particularly within the context of an emerging economy such as Brazil. In this setting, innovation-related risks are compounded by broader systemic risks that affect both firms and public policy outcomes (Gennaioli *et al.*, 2012; Lazonick and Mazzucato, 2013; Fernandes and Paunov, 2015; Leal, 2018; Buarque *et al.*, 2023).

This task becomes even more essential in countries where systemic risks amplify the inherent uncertainties of innovation, making informed decision-making particularly critical. In addition, organizations in emerging economies typically operate with more limited resources for innovation policies compared to their counterparts in developed nations. This context highlights the urgent need to develop tools that support more effective and evidence-based investment decisions in innovative projects and firms. The primary objective of this study is to develop a risk estimation model for subsidized financing granted by public organizations that promote innovation in emerging economies.

2. Theoretical framework and hypotheses

To estimate future project performance, innovation-oriented organizations rely on antecedent variables linked to technological success. These variables act as proxies for risk and inform resource allocation. The literature highlights Human Capital and Social Capital as key forms of innovation capital that reduce risk and support technological advancement in subsidized projects. This section presents the theoretical basis for two hypotheses, structured into two analytical dimensions.

Agencies managing economic subsidy programs face the ongoing challenge of assessing and mitigating the risks of funding innovation projects. Identifying variables that precede and influence technological development is essential. Human Capital and Social Capital emerge as critical factors. Research shows that technological and managerial risks are closely tied to the levels of innovation capital firms possess when applying for support (D'Este *et al.*, 2014; Stoeckicht and Soares, 2010).

2.1 Human Capital and innovation risk

Human Capital refers to the knowledge, skills, experience and educational background possessed by individuals or teams involved in innovation projects. The literature consistently identifies Human Capital as a core determinant of technological success and organizational competitiveness (McGuirk *et al.*, 2015; You *et al.*, 2021). It is linked to a firm's ability to develop dynamic capabilities, manage complex R&D processes and adapt to technological change (Amoako-Gyampah *et al.*, 2018).

Human Capital drives innovation by enhancing organizations' absorptive capacity and problem-solving abilities (Dakhli and De Clercq, 2004). This is especially crucial in emerging economies, where skilled labor increases project flexibility, reduces uncertainty and speeds up technology adoption (Morrison *et al.*, 2008). Well-qualified teams are thus better equipped to advance technologies through the stages defined by the Technology Readiness Level (TRL) framework (Olechowski *et al.*, 2020).

Beyond technological advancement, Human Capital plays a significant role in managing risk—particularly the effectiveness and efficiency dimensions of risk. Effectiveness risk refers to the likelihood that a project will achieve its intended outcomes, whereas efficiency risk relates to the ability to do so within resource and time constraints. Human Capital mitigates both types of risk by improving the quality of decision-making, increasing responsiveness to unforeseen challenges and facilitating the alignment between technical execution and strategic goals (Unger *et al.*, 2011). Technically proficient and experienced team members are more capable of adapting to shifting demands and optimizing workflows, thus reducing delays, minimizing errors and increasing overall project reliability.

In emerging economies, Human Capital is vital for reducing innovation risks, as access to skilled labor supports the adoption of new technologies and processes. Technically proficient workers adapt more easily to rapid change, helping to manage uncertainty in product and service development (Morrison *et al.*, 2008). In addition, Human Capital fosters a culture of innovation through idea exchange and collaboration, enhancing a firm's innovation capacity and competitiveness (World Bank, 2010):

Hypothesis 1(H1). The Human Capital of the project teams of innovative technological solutions influences the effectiveness and efficiency risk levels.

2.2 Social Capital and innovation risk

Social Capital refers to the value of networks, trust and shared norms that support coordination and knowledge exchange (Nahapiet and Ghoshal, 1998; Putnam, 2000). It fosters innovation by helping firms access external knowledge, form partnerships and co-create value with stakeholders like universities, suppliers and consortia (Lechner, Dowling and Welpe, 2006; Franco, Câmara and Parente, 2017).

Because innovation rarely occurs in isolation, companies embedded in dense, trustworthy networks are better equipped to manage the uncertainties of R&D, particularly in dynamic markets. The structural, cognitive and relational dimensions of Social Capital strengthen innovation capacity by reducing transaction costs, fostering trust and allowing faster responses to technical or market challenges (Iturrioz *et al.*, 2015; Duodu and Rowlinson, 2020).

The literature also highlights Social Capital's critical role in the technological development of innovation projects (Petrou and Daskalopoulou, 2013). A firm's innovation capacity depends not only on internal Human Capital but also on knowledge shared through internal and external networks. These networks form the Social Capital available to projects. By leveraging these relationships to acquire, share and coordinate information, companies can reduce uncertainty and better manage innovation risks.

An expanding body of research emphasizes Social Capital's essential role in fostering and managing innovation at the firm level. Its structural, relational and cognitive dimensions shape managerial and innovative capacities in complementary ways, supporting technological progress (Iturrioz, Aragón and Narvaiza, 2015; Franco, Câmara and Parente, 2017; Duodu and Rowlinson, 2020). Strategic network alliances, though varying in impact, are widely seen as key drivers of innovation (De Propris, 2000). Furthermore, the ability to develop and mobilize Social Capital has been linked to increased economic activity and stronger innovation outcomes (Lechner, Dowling and Welpe, 2006; Ince, Imamoglu and Karakose, 2023).

Social Capital—seen as networks, trust and norms of reciprocity—plays a key role in reducing innovation risks, especially in emerging economies. Strong networks improve the flow and quality of knowledge critical to developing, sharing and applying innovative solutions (Nahapiet and Ghoshal, 1998). Trust among firms, universities and research institutions promotes collaboration and problem-solving, creating a supportive environment for innovation (Putnam, 2000). In addition, robust Social Capital can attract investment and mobilize resources, easing financial and operational risks in early-stage projects (Woolcock and Narayan, 2000).

Social Capital plays a key role in managing technological and management risks in innovation projects by enhancing coordination, knowledge exchange and trust among team members. Strong networks facilitate faster responses to technical challenges by providing access to external expertise, reducing uncertainty (Iturrioz, Aragón and Narvaiza, 2015). Social Capital also improves effectiveness risk by supporting collaborative problem-solving and efficiency risk by streamlining communication and decision-making (Duodu and Rowlinson, 2020). In terms of management risk, trust-based relationships ensure better goal alignment and clear responsibility distribution (Franco, Câmara and Parente, 2017). In emerging economies, where institutional gaps and resource constraints are common, strong Social Capital helps firms navigate uncertainties, enabling them to leverage informal coordination and mobilize resources effectively (Woolcock and Narayan, 2000; Petrou and Daskalopoulou, 2013):

Hypothesis 2(H2). The Social Capital of the project teams of innovative technological solutions influences the effectiveness and efficiency risk levels.

2.3 Analytical framework

To develop the theoretical framework for this study, a conceptual model was created to define the variables, their causal relationships and the hypotheses to be tested. This framework, shown visually and descriptively in Figure 1, highlights the key constructs and relationships guiding the empirical analysis.

The proposed framework is grounded in the premise that organizations promoting innovation must first evaluate how subsidized financing can be used to assess associated risks. In this study, we propose that such risk is intrinsically linked to the technological advancement potential of the funded projects and their capacity to generate market value.

To operationalize the assessment, the TRL scale (Belz *et al.*, 2019; Bruno *et al.*, 2020; Olechowski *et al.*, 2020) was used to evaluate the technological maturity of beneficiary projects. As shown in Figure 1, risk perception aligns with the TRL level: higher TRL levels indicate lower technological risk, and vice versa (Ozdemir *et al.*, 2019). Projects progressing through higher TRL levels, particularly at lower costs, are viewed as yielding better outcomes for promoting organizations and presenting lower risk.

The original TRL scale had seven levels, with Level 1 representing basic concepts and Level 7 the prototype demonstration of a complex system. In 1995, Levels 8 and 9 were added, creating the current nine-level model (Olechowski *et al.*, 2020). To achieve a given TRL, a project must meet the criteria for that level and all preceding ones. Each level represents a stage of technological maturity, with increasingly complex requirements to validate progress. The TRL framework is widely used to assess when a technology is mature enough for practical use and commercialization (Tomaschek *et al.*, 2016; Bezerra, 2021).

Funding organizations play a crucial role in the innovation ecosystem but often face significant risks related to the technological development of supported projects. A major challenge is their limited visibility into the actual technological maturity of funded solutions (Soares and Prete, 2018; Buarque *et al.*, 2023). Project outcomes are often uncertain, particularly concerning technological advancements expected by project managers

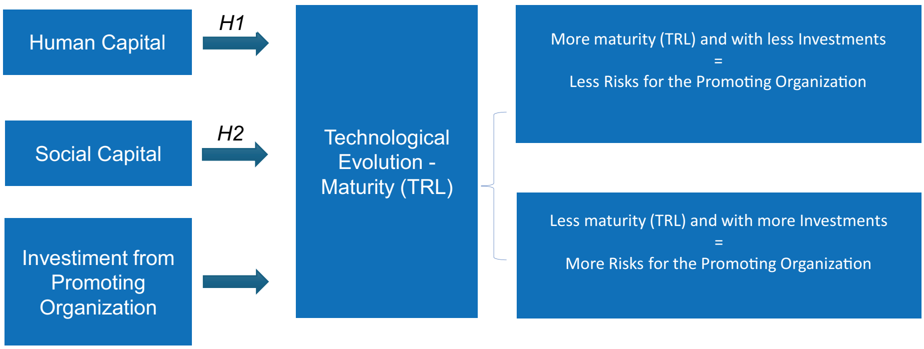

Figure 1. Analytical framework
Source: Authors' own work

(Vedovello and Figueiredo, 2005; Popa, Soto-Acosta, and Palacios-Marqués, 2022). These uncertainties represent a key risk for funding organizations. When expected results fail to materialize, the decisions made may deviate from both the intended outcomes and the broader public policy goals (Lundvall and Borrás, 2006; Rosário *et al.*, 2022).

Considering the points previously discussed, we are now in a position to formulate more robust assumptions for this research.

Assumption 1. The level of technological evolution (or maturity) of projects supported by innovation-promoting organizations can serve as an indicator of risk. Projects that achieve higher levels of technological advancement are more aligned with the objectives of these organizations, as they demonstrate greater potential to fulfill their intended purpose. Therefore, greater technological maturity may be associated with lower effectiveness risk, meaning these projects are more likely to deliver the expected outcomes and contribute meaningfully to innovation policy goals.

Projects with higher TRLs are more validated, closer to market application and better aligned with user needs. These technologies are more likely to drive further innovation and present lower risks for both the project and the promoting organization. This dynamic highlight an effectiveness risk: while uncertainties remain, successful projects strengthen the organization's mission and offer significant economic and social returns. Thus, risk assessments should consider the potential impacts and long-term sustainability of projects, aligning innovation with viability.

Assumption 2. The level of investment required per unit of technological maturity (as measured by TRLs) in projects supported by innovation-promoting organizations can serve as an indicator of risk. Projects that achieve higher TRLs with lower relative investment needs demonstrate more efficient use of public resources. Consequently, they present lower efficiency risk, as they suggest that the development organization is effectively fulfilling its mission by maximizing impact with minimal expenditure.

The level of investment needed for technological advancement in projects funded by innovation organizations is a key factor in assessing efficiency risk. Projects that achieve higher TRLs with lower investments demonstrate efficient resource allocation and effective management. When less funding is required for significant progress, it indicates that the organization is fulfilling its mandate cost-effectively. This reduces financial risk and supports the long-term sustainability of initiatives. Therefore, lower investment per unit of technological progress correlates with reduced efficiency risk, maximizing the innovation impact of the organization's portfolio.

Our theoretical framework is based on a structured literature review emphasizing the role of Human Capital in technology evolution and maturity (Theoretical Basis 1 – TB1), the contribution of Social Capital to innovation outcomes (TB2) and the use of TRLs to assess technological maturity and market readiness (TB3). These foundations support our proposition that projects funded by innovation-promoting organizations are more likely to reach higher TRL stages, reducing associated risks. A summary table of key references supporting TB1, TB2 and TB3 is provided (Table 1).

3. Methods

For this research, we used a database of historical records from innovation funding calls issued by the Foundation for the Support of Scientific and Technological Development in Ceará (Funcap), an agency under the Secretariat of Science, Technology, and Higher Education. The funding, classified as subsidized public financing, supports company-led projects developing innovative technological solutions. The data set includes 14 funding calls, covering 648 companies and 1,169 project submissions from selection processes between 2008 and 2018.

Table 1. Systematic summary of the literature base for building the analytical theoretical framework

Framework base	Code used	Main authors
Human Capital positively affects technological evolution	TB1	Amoako-Gyampah *et al.* (2018); Dakhli and De Clercq (2004); McGuirk *et al.* (2015); Morrison *et al.* (2008); You *et al.* (2021)
Social capital positively affects technological evolution	TB2	De Propris (2000); Duodu and Rowlinson (2020); Franco *et al.* (2017); Ince *et al.* (2023); Iturrioz *et al.* (2015); Lechner *et al.* (2006); Nahapiet and Ghoshal (1998); Petrou and Daskalopoulou (2013); Putnam (2000); Woolcock and Narayan (2000)
Technological evolution as market readiness maturity (TRLs)	TB3	Belz *et al.* (2019); Bezerra (2021); Bruno *et al.* (2020); Ozdemir *et al.* (2019); Olechowski *et al.* (2020); Tomaschek *et al.* (2016)

Source(s): Authors' own work

Of the total submitted projects—our primary unit of analysis—284 were approved and contracted, and data were collected from a subset of 77 projects. These projects, proposed by small technology-based companies, mainly span sectors such as ICT, biotechnology, food industry engineering and renewable energy. Despite this sectoral diversity, statistical tests showed no significant differences in the dependent variables across sectors, supporting the treatment of all projects as homogeneous in terms of the technological field. The sample is non-probabilistic and convenience-based, with no prior statistical procedures used to determine its size.

The analyses were conducted using Multiple Discriminant Analysis (MDA), a statistical method for identifying risk categories and predicting whether a project proposal in future grant calls is likely to present higher or lower risk to the funding program (Hair *et al.*, 2009). MDA creates discriminant functions, which are linear combinations of independent variables that best differentiate between predefined groups. This method highlights key characteristics and statistically significant differences between groups, providing a robust framework for understanding project profiles and aiding informed decision-making by funding organizations.

MDA is ideal when the dependent variable is non-metric (nominal or categorical) and the independent variables are metric. It is commonly used to classify cases into predefined categories, such as determining the technological and management risk associated with a financed project. MDA can also predict the risk level of projects in future public innovation subsidy calls. According to Popa *et al.* (2022), MDA is a valuable selection tool, incorporating elements like organizational commitment and innovation-related capital, which are crucial for achieving significant innovation outcomes.

MDA is a classification technique that predicts group membership for a given observation based on a set of predictor variables. It uses a discriminant function, expressed as:

$$Z = a + (b_1 \cdot x_1) + (b_2 \cdot x_2) + (b_3 \cdot x_3)$$

In this study, Z represents the dependent variable, which is the discriminant score used as a proxy for the risk level. This score is derived from the TRLs, specifically the Development TRL (DTRL), Maturity TRL (MTRL) and Effective TRL (ETRL). The model includes a constant term a (the intercept), and the coefficients b_1, b_2 and b_3, which are the discriminant weights assigned to each independent variable. The independent (predictor) variables in the model are: x_1 = Human Capital (CH), x_2 = Shared Social Capital (CSh) and x_3 = Collaborative Social Capital (CSc).

This formulation allows for the identification and differentiation of projects according to their potential risk levels, facilitating more informed decision-making by innovation-promoting organizations.

In this analysis, three distinct risk models were developed, organized into two main categories: effectiveness risk and efficiency risk.

The first two models address effectiveness risk, referring to the projects' ability to achieve technological progress during the funded development period. The first model uses the indicator development TRL (DTRL), defined as the difference between the TRL at the beginning and at the end of the technological development cycle supported by the funding. This indicator directly measures the technological advancement attained throughout the project. The second model of effectiveness employs the maturity TRL (MTRL), which represents the proximity between the final TRL of the project and the maximum value on the TRL scale. Thus, this indicator indirectly reflects how close a project is to market application, serving as a proxy for its potential impact and technological maturity.

The third model concerns efficiency risk and uses the efficiency TRL (ETRL) indicator, calculated as the ratio between DTRL and the investment amount, representing the average amount of resources invested per TRL level achieved during the funding period. However, to ensure consistency across the three risk models (DTRL, MTRL and ETRL), the efficiency measure was inverted. In this inverted version, higher ETRL values indicate lower efficiency and, consequently, higher risk—thus aligning the interpretation logic of all three indicators: the higher the value, the greater the perceived risk for the promoting organization.

These indicators are proposed in this study to assess the risk associated with subsidized funding, based on the premise that projects with limited technological advancement present higher levels of risk—particularly those with a low DTRL. Projects with minimal technological evolution tend to pose greater risks due to several factors, including limited innovation capacity, reduced competitiveness and a higher likelihood of failing to meet market demands. Such projects often struggle to attract investment and qualified talent, both of which are essential for the development, implementation and success of innovative solutions (OECD, 2015).

Projects further from maximum technological maturity pose greater risks, indicated by a lower maturity TRL (MTRL), whereas those requiring higher investment per TRL advancement are riskier, as reflected by a lower ETRL. Projects with lower maturity face greater uncertainty in development, scalability and commercial viability (Davila *et al.*, 2012). They typically require more financial and human resources and longer timeframes before yielding a return on investment.

The variables DTRL, MTRL and ETRL were categorized using their tercile values: projects below the first tercile were classified as high risk, those between the first and second terciles as medium risk, and those above the second tercile as low risk. The literature lacks examples of using the TRL scale to assess the effectiveness and efficiency of projects from the perspective of public institutions promoting business innovation. This creates a gap in understanding how these institutions can evaluate risks related to achieving their intended outcomes. The proposed approach helps address this gap and meet a clear need in the field.

The models were estimated using discriminant analysis, with the categorical risk variables—DTRL, MTRL and ETRL—as dependent variables. This approach categorizes the risk of project approval into three levels (low, medium and high) based on the efficiency and effectiveness of the technological progress of funded projects. Proxy variables for Human Capital (HC) and Social Capital (SC) served as independent variables, as outlined in the equations. The dependent variables, indicating funding risk levels, were divided into three categories. Following discriminant analysis logic, a separate discriminant function was estimated for each dependent variable, resulting in three distinct risk models, as shown in equations (1) through (6) below.

Effectiveness Risk Model 1 – DTRL:

$$ZDTRLi = fj\,(HCj,\ SChj,\ SCcj) \tag{1}$$

Effectiveness Risk Model 2 – MTRL:

$$ZMTRLi = f\,(HCj,\ SChj,\ SCcj) \tag{2}$$

Effectiveness Risk Model 3 – ETRL:

$$ZETRLi = f\,(HCj,\ SChj,\ SCcj) \tag{3}$$

where:

ZDTRL, *ZMTRL* and *ZETRL* = risk proxies classified into groups based on their terciles (1 = low, 2 = medium and 3 = high risk);

HCj = proxy for the Human Capital of the jth project;

SChj = proxy for Social Capital using the network analysis indicator (hole) of the jth project;

SCcj = proxy for Social Capital using the network analysis indicator (cluster) of the jth project; and

i = (1, 2 and 3) and j = (1,…, 77).

Table 2 summarizes the hypotheses proposed in this study along with the mechanisms used for their falsification.

The following equations describe how the variables HC, SCh and SCc were calculated. The variable HC serves as a proxy to measure the Human Capital associated with each project, based exclusively on the educational level of team members. Equation (4) presents the mathematical formulation of Human Capital, where Hij represents the value assigned to the highest educational attainment of the jth member of the ith project team. Pi denotes the corresponding weight, ranging from 1 to 6, assigned to each educational level—specifically: high school, undergraduate, specialization, master’s, doctoral and postdoctoral degrees, in ascending order. In addition, V represents the financial contribution reported by the company, which is incorporated into the calculation as a control variable to account for potential firm size effects.

Table 2. Falsification of hypotheses

Hypotheses	Subhypotheses	Falsification
H1. Human Capital influences the risk of effectiveness (DTRL and MTRL) and efficiency (ETRL)	*H1a*	HC → DTRLİ
	H1b	HCj → MTRLİ
	H1c	HCj → ETRLİ
H2. Social Capital (SChj and SCcj) influences the risk of effectiveness (DTRL and MTRL) and efficiency (ETRL)	*H2a*	SChj → DTRLİ
	H2b	SChj → MTRLİ
	H2c	SChj→ ETRLİ
	H2d	SCcj→DTRLI
	H2e	SCcj → MTRLi
	H2f	SCcj → ETRLi

Source(s): Authors’ own work

This approach to estimating the Human Capital of project teams is based on established literature. Becker (1962) identifies on-the-job training and formal education as the main means of accumulating Human Capital (see equation (4)). Trostel (2004) noted that Human Capital formation exhibits increasing returns at lower education levels and diminishing returns at higher levels. As a result, educational attainment is commonly used as a proxy for Human Capital (Mariana, 2015; Lee and Lee, 2016; Passaro *et al.*, 2018). Although more robust methods exist, the choice to use education level as a proxy was mainly driven by data availability:

$$HC = \sum Hij\,.\,Pi/Vj \tag{4}$$

SCh is a proxy variable estimating the Social Capital Hole of project teams, specifically measuring the structural dimension of social capital. It reflects the extent to which a team's network contains "structural holes," or gaps in social capital, as described by Yan and Guan (2018). Higher SCh values indicate weaker social cohesion and fewer collaborative connections within the team (see equation (5)):

$$SCh = 2 - \sum j\left(Pij + \sum q,\ q \neq i,\ q \neq j\ PiqPqj\right) 2/V \tag{5}$$

SCc is another proxy variable, representing the Social Capital Clustering of team members involved in subsidized projects. It aims to measure the degree to which members of these teams are socially integrated within a cohesive and interconnected structure. This type of Social Capital is based on the concept of network closure and follows the methodology proposed by Yan and Guan (2018). In this model, vj, vk $\in$ L(i) indicates that researchers j and k have collaborative ties with actor i; jk $\in$ E signifies that j and k also collaborate with each other; and ki(ki − 1)/2 represents the maximum number of possible connections among all researchers linked to actor i, as described in equation (6). According to Yan and Guan, project teams with high levels of clustering demonstrate stronger cohesion, greater mutual trust, longer-lasting collaborations and an enhanced ability to attract new partners:

$$SCc = \frac{I\left\{ejk : vj,\ vk\ \in\ L(i),\ ejk \in E\right\}I/V}{ki\,(ki\ -\ 1)/2} \tag{6}$$

The variables SCc and SCh were estimated by constructing a network of relationships among project team members based on their technical and scientific output, including co-authorship of patents, technical products, conference papers and journal articles. These social capital indicators were calculated using UCINet software, which enabled the modeling and analysis of these collaborative networks.

In addition to the methodological descriptions, a diagram is provided to clarify the steps and phases of this study's methodology. This visual representation illustrates the pathway followed to achieve the research objectives, as shown in Figure 2.

4. Results

4.1 Descriptive statistical analysis

Analysis of the DTRL revealed that the funded projects advanced by an average of approximately 4 levels in their technologies (mean DTRL = 3.84) on a scale of 1–9. This represents an average progression of 42.67% of the total scale levels, indicating positive performance and, consequently, a low technological risk for the program. The MTRL indicator ranges from 0 to 1, with 0 indicating higher technological risk and 1 indicating lower technological risk; the average MTRL was 0.75. This suggests that the technologies of the

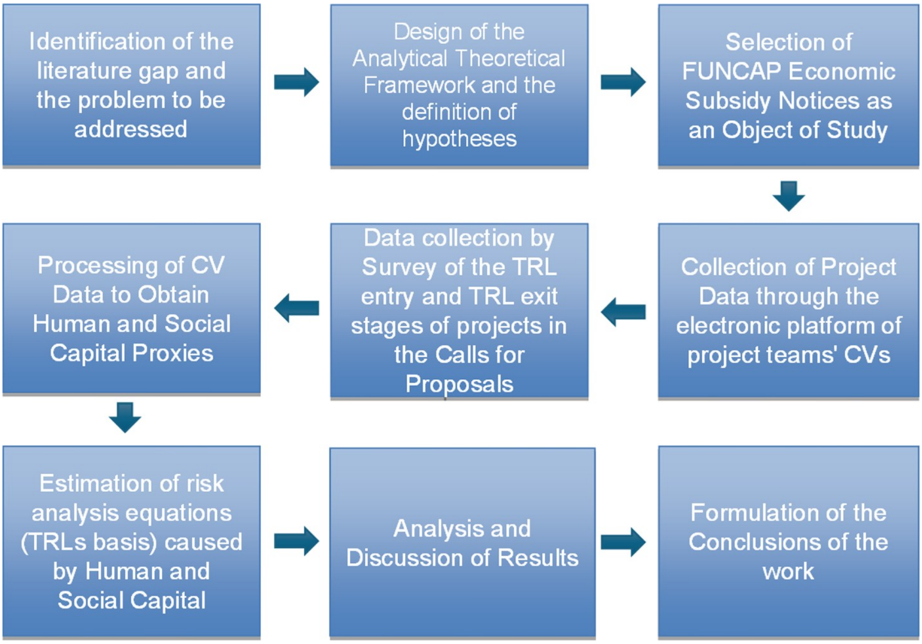

Figure 2. Diagram of the methodology phases
Source: Authors' own work

funded projects are approximately 75% aligned with the market, characterizing them as low technological risk. In addition, an analysis of the medians of the DTRL and MTRL indicators showed that 42 projects (54.5% of the sample) advanced by four or more TRL levels, whereas 46 projects (59.7%) reached at least 75% proximity to market maturity.

The ETRL indicator, which ranges from 0 to 10, presented an average value of 3.25, corresponding to an average efficiency of 32.5%. This result indicates moderate resource utilization among the funded projects, suggesting a medium to high efficiency risk in terms of the funding agency's investment strategy. In this context, ETRL reflects an inverse relationship between financial resource allocation and technological advancement—i.e. lower ETRL values signify better resource utilization and, consequently, lower financial risk for the funding organization, which typically operates under resource constraints. In addition, analysis of the median ETRL value revealed that 38 projects (49.4% of the sample) scored below 2.29, indicating that nearly half of the funded projects achieved less than 22.9% efficiency in their resource application.

The analysis of the MTRL indicator revealed a growing frequency of projects as their proximity to market increased. This pattern indicates a concentration of projects with higher MTRL values—closer to 1—suggesting that low technological risk projects are more prevalent among those supported. In parallel, the distribution of DTRL values, which measure technological maturity progression, displayed a balanced distribution. This was characterized by a higher frequency of lower progression values, coupled with the presence of higher progression values at moderate levels, symmetrically distributed around the mean. This symmetry suggests a heterogeneous yet balanced performance in terms of technological advancement among the funded projects.

This pattern also indicates that most projects exhibit low technological risk, with only a minority presenting medium levels of risk. In contrast, the ETRL indicator displays a predominant concentration of lower values, suggesting that a substantial portion of the funded projects demonstrated limited efficiency in terms of the relationship between the investment made and the resulting advancement in TRLs. This outcome points to a medium to high level of efficiency-related risk, highlighting potential concerns regarding the management and resource allocation practices within these projects.

4.2 Robustness of the promoting organization's risk estimation

A normality test was conducted to determine whether each predictor variable followed a normal distribution. The null hypothesis (H_0) assumes that the data are normally distributed, with a *p*-value greater than 0.05 indicating that the hypothesis cannot be rejected (H_0: $p > 0.05$). The Kolmogorov–Smirnov (K–S) test with Lilliefors correction—appropriate for samples larger than 30 observations—was applied. The variable HC was found to follow a normal distribution [$Z(77) = 0.100$; $p > 0.05$], whereas normality was not confirmed for the variables CSh and CSc. Nevertheless, due to the robustness of the multivariate data analysis (MDA) techniques used, and considering the sample size of approximately 80 observations, violations of the normality assumption are generally not considered problematic, as supported by key methodological literature.

To analyze the assumptions of the model, the potential for multicollinearity among the predictor variables was assessed using two standard diagnostic criteria: (i) the Tolerance Index (TI) and (ii) the Variance Inflation Factor. The results indicated acceptable values for both indicators, suggesting no significant redundancy among the independent variables. Consequently, it can be concluded that the assumption of multicollinearity is not violated, and the predictor variables are sufficiently independent for use in the multivariate discriminant analysis.

The values of Wilks' Lambda and the corresponding F-tests were calculated to assess the significance of the predictor variables. Both statistical tests operate under the null hypothesis that the group means are equal—implying that the predictor variable is not significant. However, the analytical objective was to reject the null hypothesis in favor of the alternative, which posits significant differences among the group means and, consequently, the relevance of the predictor variable.

The F-test results indicated statistical significance ($p < 0.05$) for the following predictors: (i) SCc in Model 1 [$F(2, 74) = 5.889$; $p < 0.05$]; (ii) HC [$F(2, 74) = 3.954$; $p < 0.05$] and SCc [$F(2, 74) = 3.415$; $p < 0.05$] in Model 2; and (iii) HC [$F(2, 74) = 7.568$; $p < 0.05$] in Model 3. In terms of Wilks' Lambda, the lowest values—indicating greater discriminative power—were observed for SCc ($\lambda = 0.863$) in Model 1, HC ($\lambda = 0.903$) and SCc ($\lambda = 0.915$) in Model 2 and HC ($\lambda = 0.830$) in Model 3. These findings suggest that HC and SCc are the most influential variables in distinguishing between the different risk categories modeled.

In addition to identifying the predictor variable with the highest discriminative power within each model, Wilks' Lambda statistic is also used to evaluate the significance of the discriminant functions themselves. Across all three models, the two discriminant functions were tested simultaneously, and the results confirmed that the first discriminant function in each model was statistically significant. Following this, the unstandardized coefficients for the significant discriminant functions were estimated for each predictor variable. These coefficients are essential for computing the discriminant score (Z), which is used to classify projects into one of the three risk groups associated with each model. The discriminant functions derived from these coefficients are presented in Table 3.

The results indicate that none of the main hypotheses were fully supported (see Table 3). Human Capital (HC) demonstrated an inverse relationship with both effectiveness risk, as

Table 3. Assumptions and coefficients of discriminant functions

Predictive variable	DTRL (efficacy) Low risk	DTRL (efficacy) Medium risk	DTRL (efficacy) High risk	MTRL (efficacy) Low risk	MTRL (efficacy) Medium risk	MTRL (efficacy) High risk	ETRL (efficiency) Low risk	ETRL (efficiency) Medium risk	ETRL (efficiency) High risk
Subhypotheses		*H1a*			*H1b*			*H1c*	
HC	4.058	4.882	4.043	5.593**	2.964**	6.920**	4.707***	1.648***	0.694***
Subhypotheses		*H2a*			*H2b*			*H2c*	
SCh	−0.343	−0.350	−0.392	−0.364	−0.302	−0.375	−0.306	−0.381	−0.375
Subhypotheses		*H2d*			*H2e*			*H2f*	
SCc	22.365***	25.156***	25.938***	22.506**	21.365**	24.965**	20.554	21.680	23.402
Constant (a)	−15.028	−19.891	−21.352	−15.755	−15.644	−20.721	−14.951	−15.393	−17.648

Note(s): *Significant at 10% or p-value < 0.10; **Significant at 5% or p-value < 0.05; ***Significant at 1% or p-value < 0.01
Source(s): Authors' own work

measured by MTRL, and efficiency risk, as measured by ETRL. This suggests that projects with lower levels of HC—according to the proposed measurement—are more likely to face greater risks in reaching market readiness and in efficiently utilizing the financial resources provided by the innovation-promoting organization. These findings are consistent with the existing literature, which highlights the critical role of Human Capital in supporting technological development and the success of innovative business projects (Benhabib and Spiegel, 2005; Acemoglu and Autor, 2012; López-Pueyo *et al.*, 2018; Podra *et al.*, 2020; You *et al.*, 2021).

The lack of a significant impact of human capital on DTRL can be attributed to the structured nature of technological development processes. Although human capital—skills, experience and expertise—is vital for innovation, its influence may be limited in R&D projects where standardized procedures, regulatory demands and technical milestones guide progress. As Olechowski *et al.* (2020) note, TRL advancement relies more on managing system complexity and meeting formal criteria than on individual capabilities. In publicly funded settings, where TRL progression follows predefined stages, this standardization further reduces the role of human capital in influencing DTRL outcomes.

Regarding Social Capital Hole (SCh), the results of the discriminant analysis (Table 3) revealed no significant impact on either effectiveness or efficiency risks. In contrast, Social Capital Clustering (SCc) showed no association with efficiency risk but demonstrated a negative relationship with effectiveness risk—specifically in terms of both technological advancement (DTRL) and proximity to market maturity (MTRL). These findings align with prior studies that emphasize the role of social capital—particularly cohesive and trust-based network structures—in fostering technological development and innovation performance (Landry *et al.*, 2002; Partanen *et al.*, 2008; Miguélez *et al.*, 2011; Ceci *et al.*, 2020; Ince *et al.*, 2023).

In summary, the results confirm that the significant predictor variables identified are effective in distinguishing projects across the predefined categories of the dependent variables. Moreover, the findings indicate that Human Capital influences both technological risk and the management risk associated with innovation funding in subsidized projects. In contrast, social capital plays a role in reducing technological risk through improved collaboration and knowledge exchange, but has little impact on management risk, which is more closely tied to formal processes and strategic governance.

The classification results derived from the discriminant functions are presented in the classification matrix (Table 4). For the DTRL model, 78.57% of the projects initially categorized as having low technological risk were correctly classified, demonstrating strong alignment with their original group designation. The medium technological risk group exhibited a lower but still acceptable accuracy rate of 50%, which is reasonable given the imbalance in group sizes. However, for the high technological risk group, the discriminant function (Z1) did not correctly classify any of the projects, indicating a limitation in the model's ability to distinguish projects within this category.

In the second classification matrix (MTRL), the low technological risk group achieved a high accuracy rate of 89.13%, with the majority of projects correctly classified according to

Table 4. Comparison of models by accuracy of classification matrices

Groups	DTRL (%)	MTRL (%)	ETRL (%)
Low risk	78.57	89.13	87.18
Medium risk	50.00	10.00	11.11
High risk	0.00	19.05	50.00
Overall settlement	*59.74*	*59.74*	*59.74*

Source(s): Authors' own work

their original group. However, the medium technological risk group demonstrated weak performance, with only 10 projects accurately classified and 90% of its sample misclassified into the low-risk category. The high technological risk group also showed low precision, with a correct classification rate of only 19.05%. In the final classification matrix (ETRL), classification performance improved across all groups. The low management risk group reached a high accuracy rate of 87.18%. In contrast, the medium management risk group showed limited predictive accuracy, with only 11.11% of its cases correctly classified. The high management risk group achieved a moderate classification rate of 50%, indicating a more balanced distribution compared to previous models.

When calculating the overall percentage of correct classifications—i.e. the success rate—for each of the classification matrices derived from the discriminant functions, it was observed that approximately 60% of the cases were correctly classified according to their original group assignments. To assess the discriminant power of these classification matrices, a comparison was made against chance-level classification models—random models that do not utilize discriminant functions. This evaluation used Press's Q statistic, which tests whether the classification achieved through discriminant analysis is significantly better than would be expected by chance. The results were consistent across all three classification matrices, with each yielding the same Press's Q value [$Q(1) = 96.649$; $p < 0.01$], indicating that the use of discriminant functions provided statistically superior classification performance compared to random chance.

Thus, it can be concluded that in the analyzed case, Human Capital serves as an effective discriminant of risk when using MTRL (effectiveness risk) and ETRL (efficiency risk) as proxy measures. Accordingly, hypotheses *H1b* and *H1c* are supported. With regard to Social Capital, the analysis demonstrates that it effectively discriminates risk when the Social Capital Clustering (SCc) proxy is applied and the risks are assessed using the effectiveness-related indicators and MTRL. Therefore, hypotheses *H2d* and *H2e* are also validated.

In addition, it can be affirmed that the models used in this study were capable of classifying projects into distinct levels and types of risk—as proposed—achieving an overall accuracy of approximately 60%. This level of predictive accuracy indicates that the models can function as a valuable pre-screening tool for organizations that promote innovation through project funding

By incorporating human and social capital variables from project teams, these models offer essential support for decision-making processes, enabling more informed evaluations of which projects should be prioritized for inclusion in institutional funding portfolios. It is also important to highlight that these findings are closely tied to the specific context of the research—emerging economies—where structural and resource constraints, as well as institutional characteristics, may influence the observed patterns of risk and capital impact. Therefore, the generalizability of these results should be approached with caution when considering significantly different economic or innovation environments.

5. Final considerations and management implications

Overall, the findings clearly demonstrate that higher academic qualifications among team members (Human Capital) and stronger social integration within cohesive, closed networks (Social Capital Clustering) are associated with greater innovative capacity and lower levels of both technological and managerial risk in subsidized innovation programs. This conclusion aligns with existing literature, which underscores the pivotal role of human and social capital in shaping the risk profiles of firms engaged in publicly funded innovation initiatives (D'Este *et al.*, 2014; Stoeckicht and Soares, 2010; Del Río and Kiefer, 2022; Rosário *et al.*, 2022; Buarque *et al.*, 2023).

This study contributes to public innovation policy literature by presenting a risk assessment approach for funded innovation projects from the perspective of the promoting organization. This is particularly relevant in emerging economies, where institutional capacity and resource constraints make effective portfolio management crucial. By introducing a theoretical model of relational dependency and applying an adapted measurement scale not previously used in academic research, the study offers a novel methodological contribution with clear practical implications.

The empirical findings led to the development of mathematical equations based on the predictive analysis of discriminant and logistic models. These equations serve two main purposes: they clarify the relationship between technical and management risks and the innovative capital of publicly funded projects, and they provide a predictive framework to assess the risk level of future proposals seeking public innovation support.

From a practical standpoint, the results suggest that a data-driven risk prediction tool can enhance decision-making in local innovation funding programs, particularly in emerging economies with limited public resources and high accountability pressures. By identifying high-risk projects early, funding agencies can implement targeted interventions, improving the success rate of subsidized initiatives and strengthening local innovation ecosystems.

The key contribution of this study lies not only in revealing the distinct influence of Human and Social Capital on technological and management risk but also in proposing a robust, scalable risk assessment tool. This tool demonstrates strong predictive capacity and can help public agencies in emerging economies allocate innovation funds more strategically, transparently and effectively, enhancing the legitimacy and impact of innovation policy interventions.

This study presents four notable limitations. First, the sample of tested projects was relatively limited in scope, with only 77 out of 284 analyzed projects included in the final testing phase—representing approximately 27.11% of the total. Second, while the use of the TRL scale provided a structured approach to measuring risk, its application posed certain constraints due to its relatively recent adoption in this context. Specifically, its strong technical orientation did not capture managerial dimensions that are equally critical to technological development.

Third, the analytical framework was restricted to Human and Social Capital as predictive variables. The inclusion of additional variables grounded in robust theoretical foundations could improve the accuracy of the risk classification and prediction models. This expansion could also support the assessment of a third dimension of risk—namely, the potential societal impact of the innovation projects. Fourth, this study acknowledges the absence of control variables as a limitation. While the analysis focuses on the relationships between human and social capital and different dimensions of risk and technological readiness, other contextual or organizational factors—such as firm size, industry type or prior innovation experience—may also influence the outcomes. Future research should incorporate relevant control variables to better isolate the effects of the independent variables and enhance the robustness of the findings.

For future research, it is recommended to employ larger sample sizes to improve the generalizability and robustness of the findings. Furthermore, the inclusion of additional independent variables, supported by strong theoretical foundations, would enhance the predictive accuracy and explanatory power of the relational model. Expanding the scope of risk assessment to encompass dimensions beyond effectiveness and efficiency—such as societal, environmental, or institutional risks—could also provide a more holistic understanding of the challenges associated with public innovation funding.

Acknowledgement
The authors would like to thank SECITECE (Secretariat of Science, Technology and Higher Education), SDE (Secretariat of Economic Development), FUNCAP (Ceará Foundation for Development Support) the Chief Scientist Program and the Economic Innovation Clusters Program for their indispensable support of the research and for allowing us to conduct this study.

References

Acemoglu, D. and Autor, D. (2012), "What does human capital do? A review of goldin and katz's the race between education and technology", *Journal of Economic Literature*, Vol. 50 No. 2, pp. 426-463.

Amoako-Gyampah, K., Meredith, J. and Loyd, K.W. (2018), "Using a social capital lens to identify the mechanisms of top management commitment: a case study of a technology project", *Project Management Journal*, Vol. 49 No. 1, pp. 79-95.

Antonelli, C. (2009), "The economics of innovation: from the classical legacies to the economics of complexity", *Economics of Innovation and New Technology*, Vol. 18 No. 7, pp. 611-646.

Becker, G.S. (1962), "Investment in human capital: a theoretical analysis", *Journal of Political Economy*, Vol. 70 No. 5, Part 2, pp. 9-49.

Belz, A., Terrile, R.J., Zapatero, F., Kawas, M. and Giga, A. (2019), "Mapping the 'valley of death': managing selection and technology advancement in NASA's small business innovation research program", *IEEE Transactions on Engineering Management*, Vol. 68 No. 5, pp. 1476-1485.

Benhabib, J. and Spiegel, M.M. (2005), "Human capital and technology diffusion", *Handbook of Economic Growth*, Vol. 1, pp. 935-966.

Berrutti, F. and Bianchi, C. (2020), "Effects of public funding on firm innovation: transforming or reinforcing a weak innovation pattern?", *Economics of Innovation and New Technology*, Vol. 29 No. 5, pp. 522-539.

Bezerra, W.R.P. (2021), "Development of a decision-making support application in innovation management resulting from the combination of technology readiness level (TRL) and demand readiness level (DRL) methods: the chesf case study", Master's thesis, Federal University of Pernambuco.

Blanes, J.V. and Busom, I. (2004), "Who participates in R&D subsidy programs?', The case of spanish manufacturing firms", *Research Policy*, Vol. 33 No. 10, pp. 1459-1476.

Borrás, S. and Edquist, C. (2013), "The choice of innovation policy instruments", *Technological Forecasting and Social Change*, Vol. 80 No. 8, pp. 1513-1522.

Bruno, I., Lobo, G., Covino, B.V., Donarelli, A., Marchetti, V., Panni, A.S. and Molinari, F. (2020), "Technology readiness revisited: a proposal for extending the scope of impact assessment of european public services", *ICEGOV*, pp. 369-380.

Buarque, B., Façanha Câmara, S., Paula Pinto, J.G. and Batista de Melo, J.I. (2023), "The effect of dynamic capabilities and entrepreneurial decision-making on the engagement of startups in public policies for innovation and entrepreneurship", *International Journal of Innovation (2318-9975)*, Vol. 11 No. 1.

Cannone, G. and Ughetto, E. (2014), "Funding innovation at regional level: an analysis of a public policy intervention in the piedmont region", *Regional Studies*, Vol. 48 No. 2, pp. 270-283.

Ceci, F., Masciarelli, F. and Poledrini, S. (2020), "How social capital affects innovation in a cultural network: exploring the role of bonding and bridging social capital", *European Journal of Innovation Management*, Vol. 23 No. 5, pp. 895-918.

Corder, S. and Salles Filho, S. (2006), "Conceptual aspects of financing innovation", *Brazilian Journal of Innovation*, Vol. 5 No. 1, pp. 33-76.

D'Este, P., Rentocchini, F. and Vega-Jurado, J. (2014), "The role of human capital in lowering the barriers to engaging in innovation: evidence from the spanish innovation survey", *Industry and Innovation*, Vol. 21 No. 1, pp. 1-19.

Dakhli, M. and De Clercq, D. (2004), “Human capital, social capital, and innovation: a multi-country study”, *Entrepreneurship and Regional Development*, Vol. 16 No. 2, pp. 107-128.

Damanpour, F. (1996), “Organizational complexity and innovation: developing and testing multiple contingency models”, *Management Science*, Vol. 42 No. 5, pp. 693-716.

Davila, T., Epstein, M. and Shelton, R. (2012), *Making Innovation Work: How to Manage It, Measure It, and Profit from It*, FT press.

De Propris, L. (2000), “Innovation and inter-firm co-operation: the case of the west Midlands”, *Economics of Innovation and New Technology*, Vol. 9 No. 5, pp. 421-446.

Del Río, P. and Kiefer, C.P. (2022), “Which policy instruments promote innovation in renewable electricity technologies? A critical review of the literature with a focus on auctions”, *Energy Research and Social Science*, Vol. 89, p. 102501.

Dumont, M. (2017), “Assessing the policy mix of public support to business R&D”, *Research Policy*, Vol. 46 No. 10, pp. 1851-1862.

Duodu, B. and Rowlinson, S. (2020), “The effect of social capital on exploratory and exploitative innovation: modelling the mediating role of absorptive capability”, *European Journal of Innovation Management*, Vol. 23 No. 4, pp. 649-674.

Falk, M.T. and Svensson, R. (2020), “Evaluation criteria versus firm characteristics as determinants of public R&D funding”, *Science and Public Policy*, Vol. 47 No. 4, pp. 525-535.

Fernandes, A.M. and Paunov, C. (2015), “The risks of innovation: are innovating firms less likely to die?”, *Review of Economics and Statistics*, Vol. 97 No. 3, pp. 638-653.

Fiorentin, F., Suárez, D. and Yoguel, G. (2023), “Who benefits from innovation policy? The role of firms’ capabilities in accessing public innovation funding”, *Innovation and Development*, Vol. 13 No. 1, pp. 91-108.

Franco, C., Câmara, S.F. and Parente, R.C. (2017), “Networks, R&D projects and subsidiary behavior in a host country”, *BAR-Brazilian Administration Review*, Vol. 14.

Gennaioli, N., Shleifer, A. and Vishny, R. (2012), “Neglected risks, financial innovation, and financial fragility”, *Journal of Financial Economics*, Vol. 104 No. 3, pp. 452-468.

Hair, J.F., et al. (2009), *Multivariate Data Analysis*, Bookman, Porto Alegre.

Ince, H., Imamoglu, S.Z. and Karakose, M.A. (2023), “Entrepreneurial orientation, social capital, and firm performance: the mediating role of innovation performance”, *The International Journal of Entrepreneurship and Innovation*, Vol. 24 No. 1, pp. 32-43.

Iturrioz, C., Aragón, C. and Narvaiza, L. (2015), “How to foster shared innovation within SMEs’ networks: social capital and the role of intermediaries”, *European Management Journal*, Vol. 33 No. 2, pp. 104-115.

Landry, R., Amara, N. and Lamari, M. (2002), “Does social capital determine innovation? To what extent?”, *Technological Forecasting and Social Change*, Vol. 69 No. 7, pp. 681-701.

Lazonick, W. and Mazzucato, M. (2013), “The risk-reward nexus in the innovation-inequality relationship: who takes the risks? Who gets the rewards?”, *Industrial and Corporate Change*, Vol. 22 No. 4, pp. 1093-1128.

Leal, E.A.S. (2018), “Impact assessment of the program to support research in companies (PAPPE) economic subsidy for innovation”, 153 f. Thesis (Doctorate in Production Engineering, in the Production Systems concentration area), School of Engineering, Federal University of Rio Grande do Sul, Porto Alegre.

Lechner, C., Dowling, M. and Welpe, I. (2006), “Entrepreneurship and strategic alliances, firm networks and firm development: the role of the relational mix”, *Journal of Business Venturing*, Vol. 21 No. 4, pp. 514-540.

Lee, J.W. and Lee, H. (2016), “Human capital in the long run”, *Journal of Development Economics*, Vol. 122, pp. 147-169.

Lepori, B., Reale, E. and Slipersaeter, S. (2011), "The construction of new indicators for science and innovation policies: the case of project funding indicators", *Science and Innovation Policy for the New Knowledge Economy*, Edward Elgar Publishing.

Lepori, B., Van den Besselaar, P., Dinges, M., Van der Meulen, B., Potì, B., Reale, E. and Theves, J. (2007), "Indicators for comparative analysis of public project funding: concepts, implementation and evaluation", *Research Evaluation*, Vol. 16 No. 4, pp. 243-255.

López-Pueyo, C., Barcenilla, S. and Giménez, G. (2018), "The two faces of human capital and their effect on technological progress", *Panoeconomicus*, Vol. 65 No. 2, pp. 163-181.

Lundvall, B.Å. and Borrás, S. (2006), "Science, technology, and innovation policy", in Fagerberg, J., Mowery, D.C. and Nelson, R.R. (Eds), *The Oxford Handbook of Innovation*, Oxford University Press, New York, NY.

McElroy, M.W. (2003), *The New Knowledge Management: Complexity, Learning, and Sustainable Innovation*, Routledge, London.

McGuirk, H., Lenihan, H. and Hart, M. (2015), "Measuring the impact of innovative human capital on small firms' propensity to innovate", *Research Policy*, Vol. 44 No. 4, pp. 965-976.

Mariana, I. (2015), "Consequences of the investment in education as regards human capital", *Procedia Economics and Finance*, Vol. 23, pp. 362-370.

Miguélez, E., Moreno, R. and Artís, M. (2011), "Does social capital reinforce technological inputs in the creation of knowledge? Evidence from the spanish regions", *Regional Studies*, Vol. 45 No. 8, pp. 1019-1038.

Morrison, A., Pietrobelli, C. and Rabellotti, R. (2008), "Global value chains and technological capabilities: a framework to study learning and innovation in developing countries", *Oxford Development Studies*, Vol. 36 No. 1, pp. 39-58.

Nahapiet, J. and Ghoshal, S. (1998), "Social capital, intellectual capital, and the organizational advantage", *The Academy of Management Review*, Vol. 23 No. 2, pp. 242-266.

OECD (2015), "The innovation imperative: contributing to productivity, growth and well-being", OECD Publishing.

Olechowski, A.L., Eppinger, S.D., Joglekar, N. and Tomaschek, K. (2020), "Technology readiness levels: shortcomings and improvement opportunities", *Systems Engineering*, Vol. 23 No. 4, pp. 395-408.

Ozdemir, H.I., Pinto, C.A., Unal, R., Keating, C.B. and Britcher, C. (2019), "Supporting technology selection via portfolio readiness level and technology forecasting", *Proceedings of the International Annual Conference of the American Society for Engineering Management*, pp. 1-9, *American Society for Engineering Management (ASEM)*.

Partanen, J., Möller, K., Westerlund, M., Rajala, R. and Rajala, A. (2008), "Social capital in the growth of science-and-technology-based SMEs", *Industrial Marketing Management*, Vol. 37 No. 5, pp. 513-522.

Passaro, R., Quinto, I. and Thomas, A. (2018), "The impact of higher education on entrepreneurial intention and human capital", *Journal of Intellectual Capital*, Vol. 19 No. 1.

Petrou, A. and Daskalopoulou, I. (2013), "Social capital and innovation in the services sector", *European Journal of Innovation Management*, Vol. 16 No. 1.

Podra, O., Litvin, N., Zhyvko, Z., Kopytko, M. and Kukharska, L. (2020), "Innovative development and human capital as determinants of knowledge economy", *Business: Theory and Practice*, Vol. 21 No. 1, pp. 252-260.

Popa, S., Soto-Acosta, P. and Palacios-Marqués, D. (2022), "A discriminant analysis of high and low-innovative firms: the role of IT, human resources, innovation strategy, intellectual capital and environmental dynamism", *Journal of Knowledge Management*, Vol. 26 No. 6, pp. 1615-1632.

Poutanen, P., Soliman, W. and Ståhle, P. (2016), "The complexity of innovation: an assessment and review of the complexity perspective", *European Journal of Innovation Management*, Vol. 19 No. 2, pp. 189-213.

Putnam, R.D. (2000), *Bowling Alone: The Collapse and Revival of American Community*, Simon and schuster.

Rhaiem, K. and Amara, N. (2021), "Learning from innovation failures: a systematic review of the literature and research agenda", *Review of Managerial Science*, Vol. 15 No. 2, pp. 189-234.

Rosário, C., Varum, C. and Botelho, A. (2022), "Impact of public support for innovation on company performance: review and meta-analysis", *Sustainability*, Vol. 14 No. 8, pp. 4731.

Smits, R. and Kuhlmann, S. (2004), "The rise of systemic instruments in innovation policy", *International Journal of Foresight and Innovation Policy*, Vol. 1 Nos 1-2, pp. 4-32.

Soares, F.D.M. and Prete, E.K.E. (2018), "Regulatory framework in science, technology and innovation: text and context of Law n° 13,243/2016", Belo Horizonte, Arraes Editores, 13-19.

Stoeckicht, I.P. and Soares, C.A.P. (2010), "The importance of social capital management for the development of the ability to innovate in Brazilian companies", *INGEPRO–Innovation, Management and Production*, Vol. 2 No. 10.

Tomaschek, K., Olechowski, A., Eppinger, S. and Joglekar, N. (2016), "A survey of technology readiness level users", *INCOSE International Symposium*, Vol. 26 No. 1, pp. 2101-2117.

Trostel, P.A. (2004), "Returns to scale in producing human capital from schooling", *Oxford Economic Papers*, Vol. 56 No. 3, pp. 461-484.

Unger, J.M., Rauch, A., Frese, M. and Rosenbusch, N. (2011), "Human capital and entrepreneurial success: a meta-analytical review", *Journal of Business Venturing*, Vol. 26 No. 3, pp. 341-358.

Vedovello, C. and Figueiredo, P.N. (2005), "Innovation incubator: what new species is this?", *RAE Eletrônica*, Vol. 4.

Wainova (2009), Atlas of Innovation: science/technology/research parks and business incubators in the world", WAINOVA.

Woolcock, M. and Narayan, D. (2000), "Social capital: implications for development theory, research, and policy", *The World Bank Research Observer*, Vol. 15 No. 2, pp. 225-249.

World Bank (2010), *Innovation Policy: A Guide for Developing Countries*, The World Bank.

Wu, W., Zhao, K. and Li, L. (2021), "Can government subsidy strategies and strategy combinations effectively stimulate enterprise innovation? Theory and evidence", *Economia Politica*, Vol. 38 No. 2, pp. 423-446.

Yan, Y. and Guan, J. (2018), "Social capital, exploitative and exploratory innovations: the mediating roles of ego-network dynamics", *Technological Forecasting and Social Change*, Vol. 126, pp. 244-258.

You, S., Zhou, K.Z. and Jia, L. (2021), "How does human capital foster product innovation? The contingent roles of industry cluster features", *Journal of Business Research*, Vol. 130, pp. 335-347.

Corresponding author
Elias Pereira Lopes Júnior can be contacted at: eliasjunior08@gmail.com