Research Article

Proof of Concept typology: a method for classification of PoC activities according to a technology cycle timeframe

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The paper presents the results of an experimental study aimed at creating a typology for the Proof of Concept (PoC) activities that could be more domain-specific and help practitioners to develop more effective PoC schemes. The typology has been developed by using real cases from the sample of the European Research Council (ERC) funded PoC projects. The automated subject indexing helped to generate keywords that were matched with technology descriptors from the Gartner Hype Cycles for Emerging Technologies to identify the timeframes for the funding gap according to a Hype Cycle. Accordingly, the PoC activities have been categorized into Pathbreaking PoCs, Mature PoCs and Catching-Up PoCs. The main characteristics have been identified, and further steps for the typology validation presented.

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1. Introduction

The quickening pace of technology developments has created an additional impetus to make the knowledge generation and commercialization processes that lead to the creation of innovations faster, more agile and aligned with technological cycles. McKinsey predicts that more technological progress will come in the decade ahead than in a century [1], hence the urgency for assessing funding for upcoming technologies ahead of time.

It is a broad consensus among academics and practitioners [2][3][4] that the main hurdle for increasing the generation and transfer of scientific knowledge resulting in intellectual property with a potentially high value to be realized in the emerging and existing markets is a funding gap. A gap stands between the need for funding to validate inventions on one side and the lack of market demand for high-risk undertakings on the other. Both popular and academic literature often associate this gap with the term (a metaphorical expression) "Valley of Death", which designates an initial stage in the technology life cycle where a gap between the development of new scientific knowledge and the commercial development of new products can become fatal to new ideas [5].

1.1. Study aims and research objectives

The presented study has aimed to analyse one of the funding instruments that public funding institutions and, increasingly, also research and technology organizations plan, design, and employ to help scientific research-based inventions overcome the funding gap and move closer to market. The funding scheme in question is called the PoC programme or instrument, which provides on a competitive basis a certain fixed amount of money in the form of a grant, a subsidy, or an investment for the projects that need funds to validate and commercialize new technology. The amounts can vary from ca. 20 to 60 thousand euros for initial PoC grants to more than 100 thousand for more advanced ones.

Two research objectives have been established for this study. First, to create a method that could help categorize the PoC activities according to the logic of the technological life cycles. Second, to test the approach on selected cases of the ERC PoC projects using publicly available data and create a typology of PoCs providing the basic descriptors for individual PoC types.

2. Methodology and data

2.1. Research design

Any analysis of the PoC projects has a priori limitations due to the confidentiality of the source material (let alone its availability on a scale to allow a representative sample) and the complexity of the scientific, most often interdisciplinary, fields addressed. Hence, the approach adopted for this pilot study on the typology of the PoCs has been based on using the following mechanistic causal inference. If one can assume that the PoC activities can be related to a specific technology life cycle timeframe, then one could categorize PoCs against the time expectancy of that cycle.

Three subsequent tasks have been formulated to meet these objectives. The first task was to explore, using the existing literature, the relationship between time and expectations that define a funding gap and find a way of measuring a timeframe for the current or perceived gap. The second task was to analyse the actual cases of the ERC PoC projects (using the publicly available limited information about the project duration and scope) and categorize them according to different timeframes of the expected funding gaps in each case. The third task was to describe the categories and discuss avenues for further research in validating the proposed typology and its uses for practitioners.

2.2 *Data sets*

Three datasets have been compiled to complete the tasks. Below is a brief description of each. Due to the space limitation for this paper, the data has not been included in an appendix. They could be provided upon request or shared through a public repository.

Dataset 1 in an Excel file contains details about 1225 PoC projects covering the period from 2014 to 2023 [6]. The following variables in the dataset have been used for analysis: project title, a project abstract, fields of science, and project start and end dates. Dataset 2 in an Excel file contains the information about the upcoming technology areas taken from the Gartner Hype Cycles for Emerging Technologies for the period from 2011 to 2022 (altogether 425 entries, of which 134 are unique ones); all accessed through Google search. The following variables in this dataset have been used for analysis: technology descriptor, year of appearance on a Gartner hype cycle, the minimum and the maximum years remaining to reach "the Plateau" (to be referred to as a market maturity) on a hype curve.

Dataset 3 is a subset of Dataset 1 in an Excel file containing information about 10 PoCs projects covering the period from 2016 to 2022. The cases for analysis were selected from the first 300 search results filtered down by the scientific fields of "engineering and technology/electrical engineering, electronic engineering, information engineering/electronic engineering". The following variables in the dataset have been used further: project title, URL (a reference to the project description on the Cordis website), five most relevant keywords generated from the abstract using a web-based automated subject indexing service Finto AI (see below), project start date, the matching emerging technology descriptor, the earliest and the latest year for reaching a market maturity (the latter two taken from Database 2).

3. Current state of research and design of PoCs

The existing PoC schemes, their design and their basic characterisation, have been recently quite extensively analysed [7][8][9][10][11]. Bataglia et al. (2021a) analysed the operationalisation of PoC instruments in a selected higher education institution and looked at different enablers that contribute to implementing PoCs. Further, Bataglia et al. (2021b) compared different PoCs and analysed the determinants influencing commercialisation outputs in these cases. Munari and Toschi (2021) compared the valorisation outcomes of those obtained with a PoC grant to a group of projects that applied to the PoC scheme but were not funded. The authors confirmed that the instrument was effective in the early valorisation of scientific discoveries. Munari and Wessner (2017) conducted an in-depth analysis of the ERC PoC programme to understand better how well the PoC scheme contributes to maximising the value of ERC-funded research by facilitating its commercial and social potential development. These and other academic contributions helped to map out the rationale behind the PoC schemes and their current uses by institutions from the perspective of a generic approach to the R&D life cycle and innovation. The research completed to date helped to assess individual PoC instruments according to the scope and size of funding, yet did not attempt to categorize PoCs.

The academic interest in PoC schemes has mirrored the institutionalization of this public funding instrument, which has also been adopted by leading RTOs and universities. France has been the first to introduce PoC funding in its “Investing in the Future Programme” (2009-2011). The idea has been picked up by other EU Member States (e.g., EXIST programme in Germany) before being adopted EU-wide. Since 2011 the European Research Council has been running a PoC scheme as a top-up funding opportunity for the ERC grantees aiming to bring their research results closer to market. From 2011 until June 2022 ERC funded 1469 PoCs (the success rate stood at almost 30%).

At the same time, the research and technology organizations (RTO), both public and private, have started experimenting with different approaches to foster academic entrepreneurship and commercialization by adopting a mixture of traditional product development methods such as stage-gate processes and agile processes taken from lean management and startup development. CEA, TNO, SINTEF, Tecnalia and other major RTOs have set up internal PoC schemes to provide extra funding and additional support (including mentorship and guidance with industry expertise) to the selected teams of their researchers with credible ambition to create a viable commercial product or a spin-off [12].

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4. Analysis

4.1. Timeframes in the technology life cycles

The literature shows that a funding gap for PoC activities can be expressed and measured in terms of technology or investment readiness levels, time-to-market, person-months, and other performance indicators [7][8]. However, for simplicity, this study uses a single indicator: a PoC timeframe. A PoC timeframe is a period from the start of the PoC activity until the market maturity of the relevant emerging technology field. A mature market is considered a stage where the growth rate slows to almost zero.

According to the generally accepted definition, a funding gap is the amount of money needed to fund the ongoing operations or future development of a business or project that is not currently funded with cash, equity, or debt [13]. Funding gaps can be covered by investment from venture capital or angel investors, equity sales, debt offerings, bank loans, and public funding programmes. Public and private investments attracted to address a particular funding gap are driven by various factors, of which the expectations about the potential of realising a substantial value out of the results of the R&D activities are of prime importance. Hence, one can argue that a funding gap is a function of the perceived and experienced trajectory of the technological cycle associated with technological breakthroughs and markets.

A hype cycle model introduced by Gartner Inc. in 1995 has become a standard approach to outline how the development of technologies is perceived [14][15]. It plots a generally applicable path a technology takes in terms of expectations or visibility of the value of the technology (y-axis) as related to time (x-axis). The model incorporated two distinct equations/curves adopted from behavioural psychology and technology management studies, that is a hype curve shape for human expectations about any new technology and a classical technology diffusion S-curve showing the proliferation of the technology on the market [16].

Most recently, a new approach based on the insights from neuroscience has been taken into consideration when analysing the Gartner Hype Cycle [17]. The latest research has focused on exploring expectation dynamics in early-stage innovations to explain the hype cycle phenomenon that precedes innovation adoption. Different types of expectations (emotional and logical) and speed of acceptance or abandonment of new technology have been observed as being dependent upon time [17]. The faster the time-to-market, the more emotional and rapid the acceptance of technology, which creates logical expectations and drives the hype cycle of emerging technology. Hence, the duration of any technology validation is hype cycle time and domain-dependent.

Any technology development is always a design process. The philosophers of science agree that new technology becomes accepted through five types of experiments, efforts aimed at empirically demonstrating the proper development and working of technology, including feasibility experiments, trial experiments, field experiments, comparative experiments, and controlled experiments [18]. The results of individual experimentations thus lead to obtaining proof of concept, understood as an artifact that acts in this role to demonstrate the technology at a required level of complexity. The PoC activities include verification tasks and actions (evaluation of risk assessment, product and process capabilities, compliance with requirements, proof of concept through analysis, modelling and simulation, demonstrations and tests) and validation methods (prototyping, demonstration, market tests, field trials) [19].

4.2. Subject indexing and categorization of PoCs

The categorization of PoCs is an open-ended and ad hoc process. It relies on applicants' self-reporting and keyword assignment by funding agencies' staff and expert bodies. The interdisciplinary and inter-sectorial nature of the PoC projects creates difficulties in categorizing the PoCs due to their multidisciplinary, cross-sectorial and both scientific research and market-oriented nature.

Thus, for this study, the use of an automated AI-driven subject indexing tool has been sought. The used system (Finto AI) is based on the open-source AI-driven tool Annif for indexing and classification developed by a national library consortium to categorise text in several languages, including English [20]. The tool uses text classification algorithms and a neural network model based on TensorFlow trained on the General Finnish Ontology (linked to the US Library of Congress Classification).

The subject indexing was done as follows. The text of each full abstract of the project in Dataset 3 was entered into Finto AI online tool, and the obtained five most relevant keywords were added to the project entry in Dataset 3. Then the keywords were searched in Dataset 2 containing the Gartner Hype Cycle emerging technologies. The descriptor of the corresponding technology was included in Dataset 3 to identify the match. The keywords have been manually cross-checked with the emerging technology descriptors in Dataset 2, searching for matches. The matches have been identified if the wording was synonymous or related. The EuroSciVoc taxonomy has been consulted, where there was an additional need to clarify individual keywords.

The PoCs have been categorized according to the following procedure. First, the start dates of the analysed PoC projects have been correlated with the remaining years of the corresponding matching emerging technologies using the latest reported data from the annual Gartner Hype Cycles of Emerging Technologies.

The PoCs have been classified according to the following principle. If the start of the year of the PoC activity was behind the estimated year for reaching the market maturity of the corresponding emerging technology, then the PoC was assigned to the category of "Catching Up PoC" (Type 3). If the start of the PoC activity was ahead of the emerging technology reaching market maturity by the earliest estimated date, then the PoC activity was assigned to the category of "Mature PoC" (Type 2).

If the start of the PoC activity was ahead of the emerging technology reaching market maturity by the latest estimated date by more than ten years, then the PoC activity was assigned to the category of "Pathbreaking PoC" (Type 1).

Finally, to validate the approach, each categorized PoC activity from Dataset 3 has been additionally researched using publicly available sources, trying to find details about the follow-up activities confirming one of the patterns associated with these categories. Namely, in the cases of Pathbreaking PoCs, numerous scientific activities had to be observed, which are associated with the early stages of technology development. In the cases of Mature PoCs, more applied research activities could be expected, while in the case of Catching-up PoCs, the follow-up in terms of research activities expected to be relatively minimal. Thus, a typology of PoC has been created consisting of three categories. Table 2 summarizes their main characteristics.

PoC Type	Hype Cycle stage	Time to market maturity
Type 1: Pathbreaking	Innovation/Technology Trigger Peak of Inflated Expectations	7-13 years
Type 2: Mature	Peak of Inflated Expectations Trough of Disillusionment	2-8 years
Type 3: Catching Up	Trough of Disillusionment Plateau of Productivity	0-4 years

Table 1. A preliminary typology of PoCs

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PoC No.	Keywords generated by Finto AI	Gartner descriptor	PoC Type
196345	EEG, brain, signal processing, diagnostics, measurement	Brain-computer interface	Type 1
200027	mobile communication networks, data communications networks, technology, product development, telecommunications technology	Machine-to-machine communication (M2M)	Type 2
202878	antibiotics, bacteria, antibiotic resistance, enterprises, pathogens	Biochips	Type 1
207634	video, content production, social media, content, YouTube	Social TV	Type 3
211122	energy consumption, high-speed technology, electronics, technology, consumption	Quantum computing	Type 1
211988	signal processing, lasers, optics, data transfer, polaritons	M2M	Type 2
216265	patients, metabolic disorders, public health service, wireless data transmission, monitoring	Home Health Monitoring	Type3
220480	machine learning, energy efficiency, enterprises, simulation, simulators	Low-cost single-board computers on the edge	Type 1
220708	robots, robotics, automation, recycling, industrial automation	Mobile Robots	Type 2
227183	nanostructures, sensors, diodes, beamforming, light-emitting diodes	Not covered	Type 1

Table 2. Main details of the analysed PoCs

5. Conclusions and limitations

The study has helped to create a method to quickly categorize the PoC activities using the Gardner Technology Hype Cycles for Emerging Technologies. It helped to establish a typology with three possible types for classifying PoCs into Pathbreaking PoCs, Mature PoCs and Catching-Up PoCs. Those categories can provide an additional indication of the expected timeframes of PoCs and a potential funding gap ahead. Yet, they do not offer clues for assessing the potential value of the categorized

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PoCs. The typology could help to do a quick check on any technology-based product idea where the time prospects of the market are uncertain at a given moment of the technology development. The applicability of this typology requires validation using full details of a representative sample of PoCs. However, one can only achieve that on a limited scope due to confidentiality limitations.

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